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Volume 1 | Issue 1

SIES Journal of Multidisciplinary Research and Innovation

A Peer-Reviewed Double-Blind Multi-Disciplinary Online Research Journal

SIES Journal of Multidisciplinary Research and Innovation

Editorial Note

Welcome to the inaugural issue of the *SIES Journal of Multidisciplinary Research And Innovation (SIES JMRI)*, a peer-reviewed academic research journal committed to advancing high-quality scholarly research across in varied disciplines. This journal has been established with a clear vision to nurture rigorous academic inquiry, interdisciplinary collaboration, and wide dissemination of innovative research findings from research scholars, industry experts and academicians across the globe.

SIES JMRI embraces a double-blind peer-review process to ensure the integrity, validity, and excellence of all published work. Through this commitment, we aim to provide authors with constructive and unbiased feedback, while offering readers access to well-substantiated and impactful research.

As we launch Volume 1, Issue 1, we are proud to present a platform that not only supports emerging and established researchers but also promotes open access and wide visibility so that valuable insights can reach the academic community.

As we present this issue, we extend our heartfelt gratitude to the members of the Editorial Board, peer reviewers, and all contributing for their original research. Your collective efforts have laid the foundation for what we trust will be a sustained tradition of impactful and high-quality scholarly publication.

We invite readers to explore the research presented in this issue and to contribute to future volumes through the submission of original research. We aim to build an inclusive academic forum that values quality scholarship and diverse perspectives.

Dr Koel Roychoudhury
Chief Editor
SIES Journal of Multidisciplinary Research And Innovation

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ISSN: Volume 1 Issue 1

About the Journal

The SIES Journal of Multidisciplinary Research and Innovation is a premier academic publication that provides a platform for researchers, scholars, and practitioners to share original research, innovative ideas, and critical analyses across diverse fields of study. The journal upholds the highest standards of academic rigor and scholarly excellence.

Our journal embraces a multidisciplinary approach, welcoming contributions from the arts, sciences, commerce, technology, social sciences, and humanities. We believe that the most significant breakthroughs often occur at the intersection of disciplines, where diverse perspectives converge to address complex challenges facing society today.

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Academic-industry collaboration under NEP 2020

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Abstract

The academia-industry collaboration has become important in the last few years. NEP 2020 provides opportunity for institutions to collaborate with industry for holistic development of students. Internship , market-oriented courses, incubation cells, skill based courses are some of the areas where collaboration is possible. Students benefits as it increases their employability, improves their preparedness for entering the industry. Therefore , in the long run Academia-industry collaborations have to be encouraged for achieving national goal of Viksit Bharat.

1. INTRODUCTION

Academia-industry collaboration had gained prominence in India in the last few years especially after the introduction of National Education policy (NEP) 2020. This has become relevant as an important step towards fostering innovation and skill development among the learners in institutions. As we move away from the old pedagogy of rote learning to more experiential learning, greater interaction with industries becomes important. Collaboration between academic institutions and industry is also needed for aligning the academics to the industry requirements and achieving the goals of Vikshit Bharat of the Government of India. Today, new technologies like Artificial Intelligence and Industry 4.0 requires greater collaboration among all stakeholder to empower students and help India to become a knowledge based economy. In India, the establishment of prestigious institutions like the Indian Institute of Technology(IITs) in the 1950s and 1960s laid the foundations for early collaboration. The encouragement to academic industry collaboration increased after the liberalization of the Indian economy in the 1990s. Private companies like TCS, Infosys and

Wipro started collaborating with colleges for recruitment , curriculum development and skill development. Creation of science parks and research centres were another example of collaborations. Despite these examples, the scalability remained a challenge as such collaborations were limited to elitists institutions like IITs and IIMs(MHRD, 2016). In a way introduction of NEP 2020 has been a game changer which has scope for increased collaboration for Higher educational institutions. Globally , countries like USA and UK has a vibrant academia industry collaboration which has been highly beneficial to start-ups and new technology based companies. Such collaborations are needed in India for enhancing the quality of Higher education in India.

The objective of this article is to study the opportunities and challenges for academic industry collaboration in India. Second is to explore the role of NEP 2020 in boosting such collaboration followed by identifying areas of collaboration for Higher educational institutions.

2. BENEFITS AND CHALLENGES

2.1 BENEFITS: Over the last few decades, India has witnessed increased collaboration between educational institutions and industry focussing on creating employment opportunities for learners and fostering innovation and entrepreneurship among them. Government has also played an important role by introducing schemes like Atal Innovation Mission(AIM) and Skill India.

AIM is the flagship programme of the Government of India to promote a culture of innovation and entrepreneurship in India. AIM has created Atal Tinkering Laboratories (ATLs) in schools with the objective of fostering creativity among the young minds. AIM encourages educational institutions to collaborate with start ups and industries. Similarly, Skill India is designed to promote technical and vocational training among the youth. It aims at skilling and up skilling of youth and tries to bridge the industry academia gap. It focusses on increasing employment opportunities and entrepreneurship opportunities.

Academic industry collaboration has several benefits to institutions. The primary benefit to students comes from increased employability. Institutions can have tie-ups with industry for placements and internship opportunities. There is scope of creation of industry-academic innovation hubs which will help in fostering research-based learning. Entrepreneurship is another area which will get boost through such collaboration. They can become launch pad for student led venture with industry experts playing the role of mentors.

Following is some of the **important benefits** of academic and industry collaboration.

1. **Understanding real life scenarios:** One of the main areas of focus of academia-industry collaboration is to apply academic knowledge to real life situations. Students are encouraged to do live projects, case studies and internships which helps them to gain hands on experience . This helps to complement the classrooms learning along with developing of critical thinking and better communication skills. Many programs like mass media and Business Management require students to do internships with media houses and corporate sector to gain practical exposure.
2. **Exposure to industry trends:** The business world is very dynamic in nature. It is constantly evolving in nature with new trends. Classroom learning is not adequate to understand such changes. Students benefits by getting exposure to new trends and technologies. This helps the students to gain direct knowledge of industry practices and keep their education updated.
3. **Students develop practical skills:** It is very important for students to get hands on training. This is needed for students to navigate real world business challenges. Students get to interact with industry professionals and work towards developing solutions to business problems. Interaction with industry professional are also important ways to cultivate 21st century skills like communication, negotiation skills, teamwork, project planning and decision making.
4. **Increasing employability**: One of the highlights of academic-industry collaboration is the benefits that students obtain through increased employability. Students get to build professional networks. This connection is vital for their career progression. Internship opportunities gives students a practical exposure which can also translate into final placements for them. Students also gain knowledge from industry mentors.
5. **Encouraging entrepreneurship among students**: Industry collaboration plays a positive role in encouraging and fostering entrepreneurship among students. Learners are encouraged to identify gaps in services provided by industries and come with innovative solutions to these problems. They also study how industry functions which can be one of the ways to learn how to run their own businesses in future. Industry exposure provides access to new technologies and specialized knowledge based on their domain knowledge.
6. **Supporting research and innovation:** Collaboration helps to provide invaluable support to institutions in their research and innovation initiatives. Partnerships can be

formed on research projects which enhances the quality of the research work and ensures that research is done based on the industry requirement. This is very useful as academic institutions can help industries for quality testing and product design.

7. **Helps to improve institutional reputation**: Educational institutions can build their reputation by showcasing their industry connections. This helps educational institutions to attract better quality students by providing internships and placement to them and offer industry aligned education.

2.2 CHALLENGES: While academia-industry collaboration has its benefits, there are also several challenges that come in the way of successful implementation. First one is the lengthy process of Memorandum Of Undertaking(MOU) approval. Sometimes the legal process takes moths to be finalized before the collaboration can begin. Another challenge is the communication gaps as academic institutions often lack the fast-thinking industry mind -set. Teachers do not have mind-set that industry requires to implement projects in time. Another challenge is that while such collaboration is easier in the field of science and engineering, there is limited scope in the field of humanities and social sciences. There are also problems related to funding constraints as there may be requirement of funds from educational institutions to implement the collaboration. For a long time , it was only institutions like IITs and few engineering colleges that ventured towards collaboration . Slowly even regular institutions are trying for such collaboration. But it becomes a challenge for institutions located in smaller cities. Students also have to be prepared with proper training like C.V writing and interview skills.

3. ROLE OF NEP 2020 IN ACADEMIA-INDUSTRY COLLABORATION

The NEP 2020 represents a framework that is reshaping the higher education in India. It is going to be the base for India to be transformed into a knowledge economy and be a dynamic partner in the global economy. NEP 2020 emphasizes on multidisciplinary education, research orientation and skill development. NEP 2020 provides a strong foundation for academic-industry collaboration as it emphasise on internship and project based learning. One of its key feature is the promotion of industry based curriculum. The NEP 2020 advocates vocational training and experiential learning. Through the concept of Professor of Practice, NEP facilitates the students to learn from professionals with experience. All these are key reasons for institutions to collaborate with industries for promoting holistic development of the students. NEP emphasizes on students gaining practical exposure to understand workplace challenges. Institutions are encouraged to set up entrepreneurship clubs, start-up incubators, innovation club to strengthen the industry-academic ecosystem. NEP 2020 provides opportunities to work in industries while studying. Effective implementation of NEP 2020 requires a strong collaboration between industries and academic institutions.

3.1 AREAS FOR COLLABORATION

- **Introduction of market-oriented Programmes:** Higher educational institutions can introduce market oriented courses in collaboration with industry partners. Today many institutions have introduced degree programms offering which combine with international CMA and CFA course. Another type of programmes which Colleges are introducing is Apprenticeship Embedded Degree/ Diploma Programmes (AEDP). The objective of such courses is to integrate industry-based apprenticeship training into the regular Degree or Diploma programme. This enables the students to acquire full time degree along with industry experience.
- **Establishment of Incubation centres, Start-ups**: Many educational institutions collaborate with industries to establish incubation and start -up centres. This helps to provide necessary technical expertise to the students to start their start-ups. These institutes help with financial assistance, infrastructure, legal help to start such ventures.
- **Skill development** :In today's times, under the NEP 2020 guidelines, skill development among students have become vital. Institutions have tie-ups with skill councils to offer skill-based courses to students. Swayam NPTEL courses are other ways in which students can obtain skill-based courses. Coursera offers courses with industry leaders like Google and Amazon.
- **Faculty Development** : Industry experts often collaborate with faculty members to develop curriculum , deliver guest lectures and lead workshops ensuring students secure industry knowledge. NEP 2020 requires vocational based courses which can be introduced by faculties in collaboration with industry experts.
- **Developing curriculum with industry experts**: Industry experts help faculties to design courses that are aligned to industry standards. These collaboration helps to make the syllabus taught relevant and also provide the right technical knowledge that students will require. This helps the students to acquire the necessary skills that are required by the industries. By integrating industry insights into the curriculum,

educational institutions can provide students with a well-rounded education that helps to combine theoretical knowledge with practical exposure.

- **Introducing live projects and case studies:** Many institutions include industry based live projects and curriculum as part of their curriculum. This helps students to develop professional attitude where they work with industry professionals , collaborate with peers and deliver results.
- **Gust lectures and workshops**: Guest lectures and workshops can be arranged with the help of industry professionals . Such sessions will provide knowledge , trends and challenges in the business world. It helps students to prepare for life after their college. Guest lectures and workshops helps students to ask questions and engage with industry professionals. Prominent alumni can also conduct session for students sharing their experience for working in the industry and helping students to gear up for their life after college.
- **Innovation hub:** By promoting entrepreneurship, colleges acts as launch pads for student -led ventures with collaboration with industry experts. Such collaboration is possible not only in areas like artificial intelligence, healthcare , green technologies to non-technical fields like design and social sciences. Many skill Universities have been established with the objective of promoting entrepreneurship and innovation among learners.

3.2 STEPS FOR EFFECTIVE INDUSTRY-ACADEMIC COLLABORATION IN THE FUTURE

The future of academic-industry collaboration has a lot of opportunity for growth in the future. There are several steps that have to be taken to establish a successful academia-industry collaboration. There is a need to create a collaborative ecosystem that includes curriculum design, research and innovation. An important step that can be taken by institutions is to establish innovation clusters. These clusters will help to promote interdisciplinary academic work specialization in courses like artificial intelligence, green technologies and renewable energy. Collaboration should not be confined to technical institutions only, there is a need to bring more institutions offering BCOM, BSC degrees to collaborate with industries. Colleges can collaborate to address national issues like clean energy, data analytics and sustainable living. Another area that can be enhanced is create an environment for obtaining patents and copyrights. Students should also be motivated to apply for patents for new products. Funding constraints also must be sorted with Government providing funding to even students to undertake innovation. Innovation cells have to help institutions with the entire process of staring a start-up. Another important area is reducing skill gap among students by introducing industry driven courses. Global tie-ups should also be explored for future growth of institutions.

4.CONCLUSION

The benefit of industry collaboration extends beyond the student. It is a long-term partnership that institutions create with industry partners. This helps to ensure a regular flow of resources, financial assistance and opportunities for both faculties and students. These collaborations include curriculum development and creation of innovation cell. In the long run, such collaboration helps to enhance the reputation of the educational institution but also the industry collaborator. The article calls for all stakeholders like Government, industry , academia and students to come together for a successful collaboration for the benefit of students and the nation. Then only we can realize the dream of making India into a $ 10 trillion economy by 2025 and achieve the goal of Viksit Bharat.

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THE PARADOX OF SOCIAL MEDIA: CONNECTIVITY, ISOLATION, AND THE RISE OF DIGITAL ADDICTION

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Abstract

In the digital age, social media has become an integral part of daily life, transforming communication, self-expression, and global connectivity. With over 5 billion users worldwide, platforms like Facebook, Instagram, and YouTube offer unparalleled opportunities for interaction while fostering mental health advocacy and professional networking. However, this rapid integration has given rise to social media addiction, a compulsive behavior with detrimental effects on mental health, relationships, and productivity. Rooted in psychological mechanisms such as dopamine-driven rewards and the Fear of Missing Out (FOMO), excessive social media use contributes to anxiety, depression, reduced self-esteem, and feelings of isolation. This paper explores the paradoxical role of social media as both a connector and isolator, analyzing its psychological and behavioral impacts. By examining mitigation strategies, including digital detox, self-regulation, and institutional interventions, the study underscores the importance of promoting digital well-being in an interconnected world. Insights into emerging platforms, artificial intelligence, and cultural dynamics provide a foundation for future research addressing social media addiction and its broader societal implications.

Keywords: Social media addiction, Connectivity, Isolation, Mental health, Digital well-being, Fear of Missing Out (FOMO)

1. INTRODUCTION

In the digitalization age, social media platforms have seamlessly integrated themselves into daily human life, transforming modes of communication, sharing ideas, and interaction with the global community. Social media represents a technological collection that facilitates the dissemination of ideas and information among users (Dollarhide, 2024). Platforms such as Facebook, Instagram, X (formerly Twitter), and YouTube boast over 5 billion users, accounting for approximately 62% of the global population. These platforms allow people to connect and express themselves in unparalleled ways, enabling instant communication across geographic and cultural boundaries (Qiu, 2024). However, as social media becomes deeply embedded in daily routines, a pressing challenge has surfaced: ***Social Media Addiction***.

Social media addiction refers to the compulsive and excessive use of social media characterized by dependency, which disrupts personal, academic, and professional responsibilities. According to Sherer (2024), Medical Director of Addiction Psychiatry at Overlook Medical Center, Atlantic Health System, Summit, New Jersey, social media addiction is a compulsive and problematic use of social platforms. It involves an obsessive urge to check and update social media accounts, often leading to real-world relationship disruptions and functional impairments.

This phenomenon is deeply rooted in psychological mechanisms, particularly the dopamine-driven reward system that reinforces repetitive behaviors, and the Fear of Missing Out (FOMO), which compels individuals to stay perpetually engaged with online content (Andreassen, 2015). Despite its capacity to enhance connectivity, social media paradoxically intensifies feelings of isolation and loneliness, creating a psychological tension that demands comprehensive investigation (Ahmed, 2023).

The dual role of social media in fostering both connection and isolation becomes most evident in its impact on mental health (Sala *et al*., 2024). While social media provides spaces for support networks, mental health advocacy, and the sharing of experiences, excessive use has been linked to anxiety, depression, and reduced self-esteem (Keles *et al*., 2020). This paradoxical relationship raises critical questions about the role of social media in shaping contemporary psychological experiences.

As society becomes increasingly reliant on digital communication, understanding the psychological implications of problematic social media usage is imperative. This paper endeavors to unravel the intricate interplay between social media's connectivity and isolation effects. By leveraging empirical studies and theoretical frameworks, it addresses this contemporary issue. The research delves into the mechanisms underlying social media addiction, its mental health consequences, and strategies for mitigation. Through this analysis, the study aims to contribute to ongoing discussions about promoting digital well-being in an interconnected world.

While the study does not rely on primary empirical data, its originality lies in synthesizing interdisciplinary perspectives into a unified conceptual framework. By integrating psychological, behavioural, and technological dimensions, the paper offers conceptual clarity on the connectivity–isolation paradox and identifies critical directions for future empirical research.

2. METHODOLOGY

This study adopts a conceptual and narrative review approach to examine social media addiction through the lens of the connectivity–isolation paradox. As the paper does not involve primary data collection, it relies on the systematic synthesis of existing literature across interdisciplinary domains.

Relevant literature was identified through structured searches of academic databases, including Google Scholar, Scopus-indexed journals, and Web of Science. Keywords such as "social media addiction," "digital well-being," "fear of missing out (FOMO)," "social comparison," "cyberpsychology," and "online behavioural addiction" were used to identify pertinent studies.

Priority was given to peer-reviewed journal articles published between 2010 and 2024, with particular emphasis on recent and highly cited works. Studies were selected based on their relevance to psychological mechanisms, behavioural outcomes, and patterns of digital engagement.

The selected literature was thematically analyzed and organized into key conceptual categories, including drivers of addictive behaviour, psychological consequences, and mitigation strategies. This approach enables a comprehensive and integrative understanding of the phenomenon while maintaining conceptual rigor.

Although the study is non-empirical in nature, it contributes by offering theoretical integration, identifying research gaps, and proposing directions for future empirical investigation.

3. THE DUAL IMPACT OF CONNECTIVITY AND ISOLATION

3.1 Connectivity: The Positive Side

Social media has revolutionized how individuals communicate and connect with one another, offering significant benefits for both personal and professional relationships. Its multifaceted nature allows for enhanced connectivity in various spheres of life.

3.2 Keeping Long-Distance Relationships: Social media bridges geographical gaps, enabling individuals to maintain meaningful relationships with friends, family, and colleagues regardless of physical distance. Applications like WhatsApp, Facebook, and Instagram facilitate real-time video calls and updates, fostering a sense of proximity even when miles apart (Ellison *et al*., 2007).

3.3 Forming Professional Networks: Platforms like Linkedin have transformed professional networking, offering tools to connect with industry peers, employers, and potential collaborators. Social media serves as a powerful medium for career development through mentoring, job searching, and personal branding (Kietzmann *et al*., 2011).

3.4 Providing Platforms for Self-Expression and Advocacy: Social media empowers individuals to express their opinions, showcase their creativity, and share personal stories. It also acts as a catalyst for social change by amplifying voices and raising awareness on critical issues. Movements such as *MeToo* and *BlackLivesMatter* demonstrate its potential to mobilize communities and drive advocacy (Khamis *et al*., 2017).

3.5 Accessibility to Support Groups: Social media provides a safe space for individuals facing mental health challenges, chronic illnesses, or life transitions. Online support groups on platforms like Reddit and Facebook foster emotional resilience by sharing lived experiences, offering advice, and building communities of support (Naslund *et al*., 2016).

3.6 Isolation: The Negative Aspect

Despite its potential to connect, social media can paradoxically contribute to feelings of loneliness and isolation. Several factors drive these negative outcomes:

3.7 Superficial Interactions: While online relationships facilitate outreach, they often lack the depth and emotional fulfillment of face-to-face interactions. This superficiality can leave users feeling unsatisfied and disconnected, as digital communication cannot replicate the nuances of human connection (Turkle, 2015).

3.8 Cyberbullying: Social media can expose users to harassment, trolling, and cyberbullying, resulting in significant psychological distress. Victims often experience heightened feelings of vulnerability and isolation (Kowalski *et al*., 2014).

3.9 Social Comparison: The curated content on social media fosters an environment of constant comparison. Viewing idealized lifestyles and achievements can lead to feelings of inadequacy, low self-esteem, and anxiety, particularly among teens and young adults (Chou and Edge, 2012).

3.10 Time Displacement: Excessive use of social media often displaces time that could be spent on meaningful offline activities, such as pursuing goals, reading, or nurturing in-person relationships. Over dependence on digital interactions can perpetuate a sense of isolation from the physical world (Nie *et al*., 2002).

Nevertheless, it is important to acknowledge that empirical findings on social media use are not universally negative. Several studies suggest that when used actively and purposefully, social media can enhance social connectedness, provide emotional support, and even reduce perceived loneliness. For example, individuals who engage in direct communication, community participation, and support-based interactions often report more positive psychological outcomes compared to passive users. These contrasting findings indicate that the effects of social media are highly dependent on usage patterns, user intent, and contextual factors, rather than being inherently detrimental.

4. PSYCHOLOGICAL CONSEQUENCES

4.1 Mental Health Issues

Excessive social media use has significant implications for mental health, with research linking it to various psychological concerns:

4.2 Anxiety and Depression: Extensive studies have established a correlation between excessive social media use and increased levels of anxiety and depression. This relationship stems from factors such as the pressure to maintain an idealized online persona, exposure to negative interactions, and incessant comparisons to others' curated lives (Keles *et al*., 2019). These elements often lead to feelings of inadequacy and persistent worry.

It is important to note that most existing studies establish correlational rather than causal relationships between social media use and mental health outcomes. Therefore, while strong associations have been observed, causal pathways remain complex and may be influenced by mediating variables such as personality traits, usage patterns, and pre-existing psychological conditions.

4.3 Sleep Disturbances: Research indicates that late-night scrolling and prolonged exposure to blue light emitted by screens disrupt circadian rhythms, adversely affecting sleep quality and duration (Exelmans and Van den Bulck, 2017). Poor sleep contributes to reduced emotional regulation and heightened stress levels.

4.5 Reduced Self-Esteem: Social media fosters a culture of comparison, where users assess their self-worth against the highlight reels of others. This trend is linked to decreased self-esteem and body image concerns, particularly among adolescents and young adults (Nghaimesh *et al*., 2023).

4.6 Impaired Attention and Cognitive Functioning: Constant notifications and the need to multitask on social media platforms fragment users' attention spans, making it challenging to focus on complex tasks. Over time, this behavior can impair cognitive functioning and overall productivity (Cain and Gradisar, 2010).

4.7 Behavioral Impacts

Social media addiction also manifests in behavioral patterns that disrupt both personal and professional spheres:

4.8 Procrastination and Reduced Productivity: The addictive allure of social media often results in time mismanagement, with individuals prioritizing online interactions over essential responsibilities. This habit negatively impacts academic achievements and workplace performance.

4.9 Interpersonal Conflicts: Excessive engagement with social media can strain offline relationships. For example, prioritizing virtual interactions over face-to-face conversations can lead to feelings of neglect among family and friends, causing emotional disconnect and friction (Jiang *et al*., 2019).

4.10 Overdependence on Virtual Validation: The constant pursuit of likes, comments, and shares fosters an overreliance on external validation. Such dependency diminishes intrinsic motivation and emotional resilience, leaving individuals more vulnerable to criticism or a lack of online engagement (Nesi and Prinstein, 2015; Bradley *et al*., 2018).

5. STRATEGIES FOR MITIGATION

5.1 Personal Habits

- **Deliberate Use:** Limiting social media usage is an essential step to mitigate its addictive potential. Individuals can set specific daily time limits or designate screen-free hours, such as during meals or before bedtime. Research indicates that such practices promote self-regulation and reduce excessive screen time (Twenge and Campbell, 2018).
- **Digital Detox:** Periodic disengagement from social media allows individuals to reset their usage patterns and reflect on their dependency. This could involve weekend breaks or extended duration during vacations. Studies have shown that digital detox improves mental clarity, reduces stress, and enhances overall well-being (Roberts and David, 2016).
- **Self-awareness:** Recognizing triggers and patterns of problematic use enables individuals to make informed decisions. For example, identifying emotions like boredom or loneliness that lead to excessive social media use can encourage alternative coping mechanisms such as pursuing hobbies or engaging in physical activities (Andreassen, 2015).
- **Professional Support:** Therapy or counseling can aid individuals struggling to regulate their social media use. Cognitive-behavioral therapy (CBT) has proven effective in reshaping users' perspectives, addressing underlying issues, and fostering healthier practices (Young, 2017).

5.2 Institutional and Social Interventions

- **Educational Programs:** Digital literacy initiatives incorporated into academic curricula can prepare individuals to navigate social media responsibly. Workshops on the psychological effects of social media and guidance on responsible use have demonstrated effectiveness in fostering healthier online habits (Cain and Gradisar, 2010).

- **Platform Design:** Technology companies play a pivotal role in mitigating social media addiction by integrating user-friendly features. Tools such as screen time trackers, break reminders, and limited auto-play options have been associated with reduced compulsive usage and enhanced user satisfaction (Rahayu *et al*., 2023).
- **Parental Guidance:** Parents can help younger users develop balanced social media habits by setting clear usage guidelines, monitoring online activities, and encouraging offline interactions. Evidence suggests that parental involvement fosters healthier digital behaviors in children (Livingstone and Helsper, 2008).

5.3 DIRECTIONS FOR FUTURE STUDY

- Investigate long-term mental health outcomes related to chronic social media addiction, including anxiety, depression, and cognitive decline across age groups.
- Explore how cultural contexts influence social media usage, its psychological effects, and coping mechanisms.
- Assess how newer platforms like TikTok and Threads differ from traditional platforms like Facebook and Instagram in terms of addictive properties.
- Examine how AI-driven algorithms, such as personalized feeds and recommendations, exacerbate social media addiction and explore design solutions to mitigate this issue.
- Evaluate the effectiveness of digital literacy programs in reducing social media addiction among youth and promoting healthy online behaviors.
- Analyze the impact of social media addiction on family dynamics, romantic relationships, and workplace interactions.
- Use neuroimaging studies to investigate structural and functional changes in the brain resulting from prolonged social media use.
- Compare the effects of various digital detox strategies on mental health and behavior over short and long periods.
- Study generational variations like Gen Z, Millennials, Gen X in susceptibility to social media addiction and its psychological consequences.
- Identify factors such as emotional intelligence and offline support networks that buffer against the negative effects of social media addiction.

- Examine how gamification elements in social media platforms encourage addictive behaviors, particularly among younger users.
- Evaluate the effectiveness of government and platform-level policies, such as screen time alerts, in curbing social media addiction.
- Investigate how emerging technologies like VR and the Metaverse influence social media usage patterns and addiction risks.
- Explore the relationship between constructed digital identities and their influence on users' self-perception and mental health.
- Analyze the ethical responsibilities of social media companies in addressing addiction and promoting user well-being.

6. LIMITATIONS

This study is conceptual in nature and relies on the synthesis of existing literature rather than primary empirical data. As such, the findings are dependent on the scope and interpretation of selected studies. Additionally, LIMITATIONS

the rapidly evolving nature of social media platforms may limit the temporal applicability of certain observations. Future empirical research is therefore necessary to validate and extend the conceptual insights presented in this paper.

7. CONCLUSION

Social media has undoubtedly transformed the way individuals connect, communicate, and share ideas, bringing unparalleled convenience and accessibility to the digital era. While it offers significant advantages, such as fostering long-distance relationships, professional networking, and mental health advocacy, its pervasive integration into daily life has also given rise to serious concerns, particularly social media addiction. This phenomenon, driven by psychological mechanisms like the dopamine reward system and Fear of Missing Out (FOMO), disrupts personal, academic, and professional spheres, often exacerbating feelings of isolation, anxiety, and reduced self-esteem.

The dual role of social media in fostering both connectivity and isolation underscores the need for a nuanced understanding of its psychological implications. Strategies such as deliberate use, digital detox, and professional support, alongside institutional interventions like digital literacy programs and platform design improvements, can mitigate its adverse effects. Furthermore, future research exploring cultural differences, the role of artificial intelligence, and emerging platforms like VR and the Metaverse will provide deeper insights into addressing social media addiction.

However, it is important to recognize that the psychological impact of social media is not uniformly negative. Emerging research suggests that moderate and purposeful use can enhance social support, strengthen relationships, and improve well-being, particularly among individuals with limited offline interaction opportunities. These contrasting findings indicate that the effects of social media are contingent upon usage patterns, individual differences, and contextual factors, thereby necessitating a more nuanced and balanced interpretation.

As society continues to navigate the complexities of the digital age, it is imperative to balance the benefits of social media with mindful usage practices. Promoting digital well-being through education, policy reforms, and personal responsibility will ensure that social media remains a tool for empowerment rather than a source of dependency.

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PREDICTING SLEEP QUALITY VIA BEHAVIOURAL AND LIFESTYLE INDICATOR ANALYSIS USING MACHINE LEARNING

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ABSTRACT

Sleep deprivation has become a critical public health concern, increasingly driven by modern lifestyle habits such as excessive screen time and high stress levels. While traditional clinical studies often focus on medical disorders like Sleep Apnoea, this research shifts the focus to predicting sleep quality by analysing behavioural and lifestyle indicators using machine learning. A primary dataset was collected via a structured survey capturing key metrics including sleep duration, latency, and bedtime procrastination, with a specific demographic emphasis on Gen Z and Millennials to reflect digital-age habits. A comparative analysis of six machine learning classifiers ranging from linear models to ensemble methods was performed and optimised using GridSearchCV. To ensure model reliability, the study employed a rigorous validation framework, introducing a custom "Overfitting Gap" threshold to guarantee generalisability. The results demonstrate that the Random Forest classifier achieved superior performance with 85.19% accuracy and an ROC-AUC of 0.88, proving more effective at handling complex, non-linear lifestyle data than traditional linear models. Crucially, Feature Importance analysis identified Sleep Duration, Bedtime Procrastination and Stress Level as the most significant predictors, highlighting that psychological behavioural patterns are as critical as biological markers in determining sleep health. This study provides a data-driven basis for personalised health interventions and future mobile-based sleep monitoring systems.

Keywords: Bedtime Procrastination, GridSearchCV, Machine Learning, Overfitting Gap, Random Forest, Sleep Deprivation

1. INTRODUCTION

In the digital age, sleep patterns have shifted drastically due to technological ubiquity and changing social norms. While often associated with younger demographics, the phenomenon of "bedtime procrastination" - the voluntary delay of sleep to engage in leisure activities like scrolling on smartphones - has increasingly permeated the lifestyles of the general population. Traditional clinical studies often prioritize medical disorders like Sleep Apnoea, frequently neglecting the behavioural roots of sleep deprivation that affect individuals across diverse life stages.

The objective of this project is to develop a predictive system that correlates daily habits (e.g., caffeine intake, exercise, dinner timing) with sleep quality. Unlike studies limited to specific cohorts, this research leverages machine learning to analyse lifestyle factors across a wide demographic spectrum, ranging from individuals under 18 to those over 65. By doing so, we aim to identify the specific habits that contribute most significantly to poor sleep, providing a robust, data-driven basis for personalised health interventions applicable to a broader society.

2. LITERATURE REVIEW

The analysis of sleep quality has increasingly shifted from clinical methods to data-driven Machine Learning (ML), utilizing lifestyle indicators and physiological data. A significant portion of recent research highlights the superiority of ensemble methods. Bhatti et al. (2025) and Rahman et al. (2025) validated the efficacy of Random Forest and Gradient Boosting on lifestyle datasets, achieving accuracies of 98.67% and 97.33%, respectively. Rahman et al. specifically noted the value of optimizing these approaches for sleep disorder diagnosis. Similarly, Taher and Ayon (2024) found Gradient Boosting to be the best performing model (93.80%) in a comparative analysis, though they noted potential overfitting risks due to smaller datasets. Further supporting this trend, Maruf & Chowdhury (2025) achieved 90.10% accuracy using CatBoost, emphasizing the importance of multi-factor systems, while Islam et al. (2025) and Sahu et al. (2025) confirmed the robustness of Random Forest in predicting sleep disorders based on occupational and stress factors, with Islam et al. achieving up to 96.70% accuracy.

While ensemble models dominate, the trade-off between complexity and performance remains a key debate. Wang (2024) explored Deep Learning architectures like CNNs and LSTMs, suggesting high potential for feature extraction, though often at a higher computational cost. Conversely, Ekim and Koklu (2026) demonstrated that traditional Artificial Neural Networks (ANN) could achieve 92.92% accuracy, outperforming SVM and Random Forest in specific disorder classifications. Lee et al. (2025) also utilized Artificial Neural Networks alongside digital biomarkers to predict sleep quality with 90.40% accuracy, utilizing LSTM models to analyze sequential data patterns effectively.

The source of data significantly impacts model viability. Credico et al. (2024) utilized biofeedback sensors (Heart Rate Variability, Skin Temperature) to predict sleep quality, achieving 83.40% accuracy with SVM, though the approach requires intrusive sensors. In contrast, Bleumink's dissertation (2023) highlighted that smartphone application usage alone is a poor predictor (~19% accuracy), suggesting that mere app duration is insufficient without content context. Complementing these findings, Runtong et al. (2025) used logistic regression to statistically model lifestyle impacts, reinforcing the consensus that combining physiological data with broad lifestyle metrics - rather than relying on single-source data - yields the most reliable predictive systems.

Table 1: Summary of Research Papers (2023–2026)

	Paper Title	Algorithms Used	Accuracy	Future Scope	Research Gap
Bhatti et al. (2025)	Modeling Sleep Health and Lifestyle Using Supervised Learning	Random Forest (Best), SVM, KNN	98.67%	Integration with IoT devices for real-time monitoring.	Limited to specific dataset; lacked real-time sensor integration.
Rahman et al. (2025)	Improving Sleep Disorder Diagnosis Through Optimized ML	Gradient Boosting (Best), Voting	97.33%	Testing on clinical populations and real-time data.	Focused on algorithmic tuning rather than feature causality.
Taher & Ayon (2024)	Exploring Sleep Disorders: A	Gradient Boosting (Best), RF	93.80%	Hybrid Deep Neural Networks (CNN-LSTM).	Small dataset (400 records) may lead to overfitting.

	Comparative Analysis				
Ekim & Koklu (2026)	Classification of Sleep Disorders Using Machine Learning	ANN (Best), SVM, Random Forest	92.92%	Mobile application for early self-diagnosis.	Biased towards specific disorders (Insomnia/Apnoea).
Maruf & Chowdhury (2025)	A Multi-factor based Sleep Quality Prediction System	CatBoost (Best), Random Forest	90.10%	Include doctor scheduling and personalised recommendations.	Relied heavily on subjective survey data.
Lee et al. (2025)	Predicting Sleep Quality with Digital Biomarkers and ANN	LSTM (Best), Random Forest	90.40%	Exploring LF/HF ratio as a digital biomarker.	Weak correlations with previous nights' data.
Credico et al. (2024)	Predicting Sleep Quality through Biofeedback	SVM (Best), KNN, Decision Tree	83.40%	Contactless technologies for ergonomic applications.	Relied on intrusive biofeedback sensors.
Bleumink (2023)	Predicting Sleep Quality From Smartphone Application Usage	XGBoost, Random Forest	~19%	Content analysis of app usage rather than just duration.	App categories alone were poor predictors.
Wang (2024)	Application and Analysis of Deep Learning on Sleep Quality	Deep Learning (CNN, LSTM)	N/A	Real-time edge computing implementation.	High complexity/cost compared to traditional ML.
Runtong et al. (2025)	Predicting the impact of lifestyle on sleep health	Logistic Regression	N/A	Longitudinal studies on changing lifestyle habits.	Cross-sectional nature limits causal inference.
Islam et al. (2025)	Sleep Disorder Prediction System Using Machine Learning	Random Forest (Best), KNN	96.70%	Testing on real-time data streams.	High accuracy likely due to SMOTE oversampling.
Sahu et al. (2025)	Analysis of Sleep Health	Random Forest, SVM	~93.0%	Longitudinal study on job impact.	Heavy reliance on occupation as a stress proxy.

	and Lifestyle Factors				

3. METHODOLOGY

3.1 Data Collection & Pre-processing

Data was collected via a structured survey (survey.csv) focusing on daily habits.

- **Data Cleaning:** Irrelevant columns were dropped, and features were renamed for clarity (e.g., "Gender", "Screen_Time", "Caffeine_Cups").
- **Demographics:** The dataset represents a diverse demographic spread. While the majority of respondents belonged to the 18-25 age group (52.3%), there was significant representation from the 26-45 age group (26.2%) and older demographics, ensuring the model's applicability across different life stages. The gender distribution was nearly balanced with 51.4% Male and 48.6% Female respondents.
- **Binning:** Continuous variables were categorised to reduce noise. "Stress_Level" was binned into Low, Moderate, and High, while "Sleep_Quality" was binned into Poor (61.7%) and Good (38.3%).

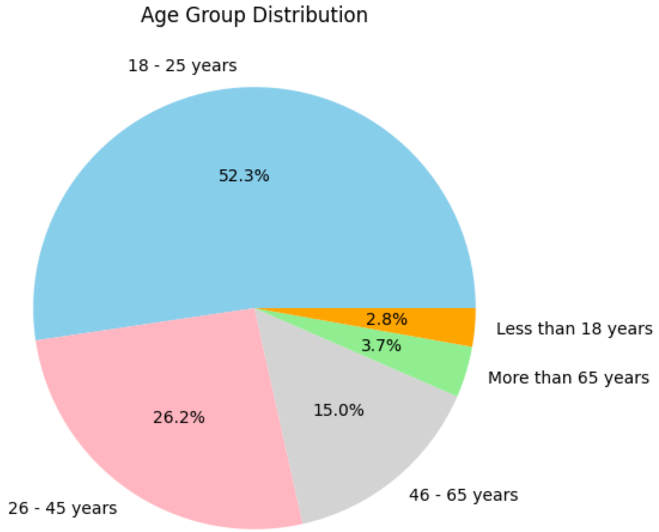

Figure 1: Age distribution of survey respondents.

3.2 Exploratory Data Analysis (EDA)

Visualisations were generated to understand distributions. A Correlation Matrix was computed to check for multicollinearity among the lifestyle variables.

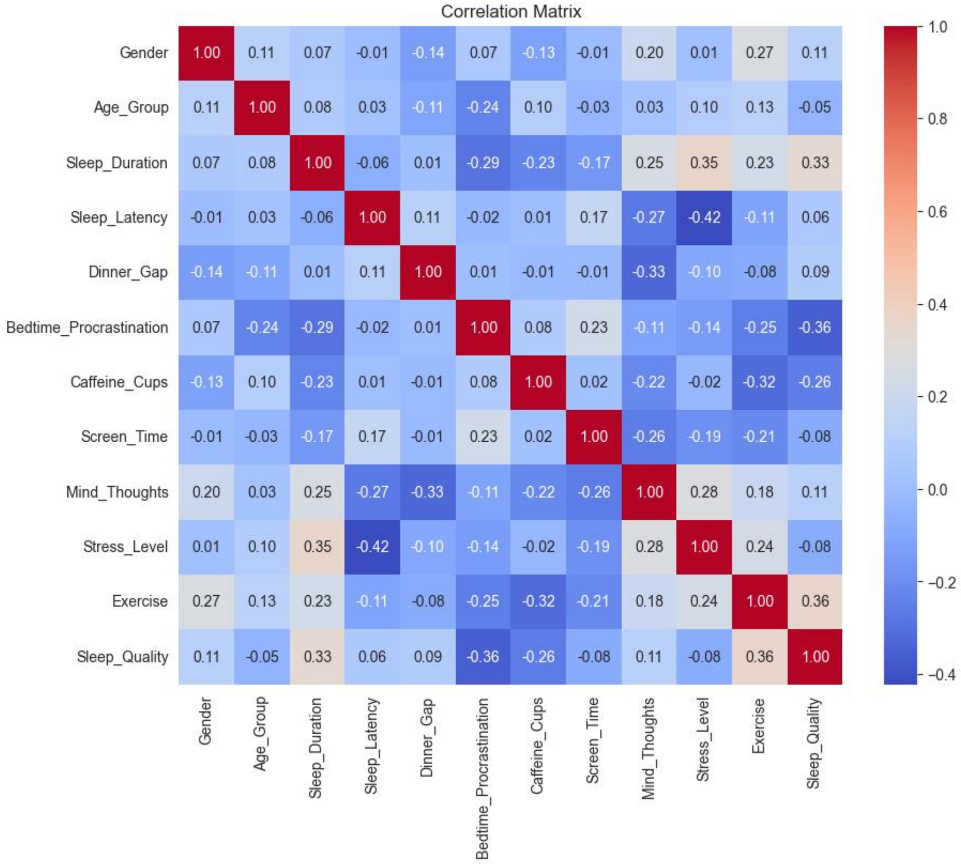

Figure 2: Correlation matrix of lifestyle variables.

3.3 Model Implementation

These ML algorithms were used to build models and test:

- **Gaussian Naive Bayes:** A probabilistic baseline.
- **Logistic Regression:** For establishing linear relationships.
- **K-Nearest Neighbors (KNN):** Distance-based classification.
- **Support Vector Machine (SVM):** Effective for high-dimensional margins.
- **Decision Tree:** For rule-based interpretability.
- **Random Forest:** An ensemble method to reduce variance.

3.4 Optimisation & Evaluation Strategy

These techniques were used to optimise models and evaluate them:

- **Hyperparameter Tuning:** GridSearchCV was applied to every model with StratifiedKFold (5 splits) to find optimal parameters (e.g., C for SVM, n_neighbors for KNN).
- **Feature Importance Method:** To ensure interpretability across all algorithms, feature importance was derived using different techniques: native Gini impurity for tree-based models (Random Forest, Decision Tree), Coefficient magnitude for linear models (Logistic Regression), and Permutation Importance for non-linear models (SVM, KNN, Naive Bayes) where intrinsic feature ranking is not available.
- **Overfitting Detection Logic:** To ensure the model did not simply memorise the survey data, a strict validation logic was implemented mathematically as follows:

Gap = Training Accuracy - Testing Accuracy

The model status was determined using the following threshold:

- If Gap > 0.15 then Flagged as "Likely Overfitted".
- If Training Accuracy < 0.50 then Flagged as "Likely Underfitted".
- Otherwise: Flagged as "Fitted Correctly".

This logic ensures that only models with generalisable patterns are selected for the final comparison.

4. RESULTS AND ANALYSIS

4.1 Model Performance

The performance of all models was tabulated and sorted by weighted F1-Score to account for class imbalance.

- **Random Forest** achieved the highest performance with an Accuracy of 85.19% and a weighted F1-Score of 0.85, proving its robustness in handling complex lifestyle data.
- **Support Vector Machine (SVM)** followed closely with an Accuracy of 81.48%.

Table 2: Model Performance of Different Algorithms

Sr. No.	Model	Accuracy	Precision	Recall	F1 Score
1	Random Forest	0.851852	0.883041	0.851852	0.845752
2	Support Vector Machine	0.814815	0.82716	0.814815	0.810005
3	K-Nearest Neighbors	0.777778	0.780392	0.777778	0.774621
4	Logistic Regression	0.777778	0.798246	0.777778	0.768627
5	Decision Tree	0.740741	0.823232	0.740741	0.711888
6	Gaussian Naïve Bayes	0.703704	0.740741	0.703704	0.679012

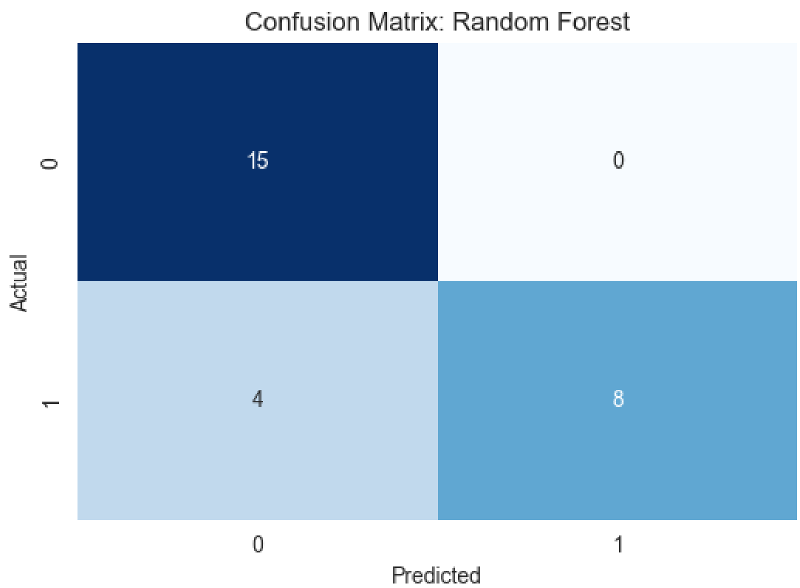

Figure 3: Confusion Matrix of Random Forest Classifier Model.

4.2 Feature Importance

Feature Importance plots revealed distinct drivers of sleep quality for the best-performing models:

- **Top Predictors:** For the Random Forest model, 'Sleep_Duration' was the most critical feature, followed closely by 'Bedtime_Procrastination' and 'Stress_Level'.
- **Behavioural vs. Stress:** Unlike linear models where 'Bedtime_Procrastination' was the sole dominant feature, the Random Forest model successfully integrated biological markers (Sleep_Level) with behavioural habits, providing a more holistic prediction.

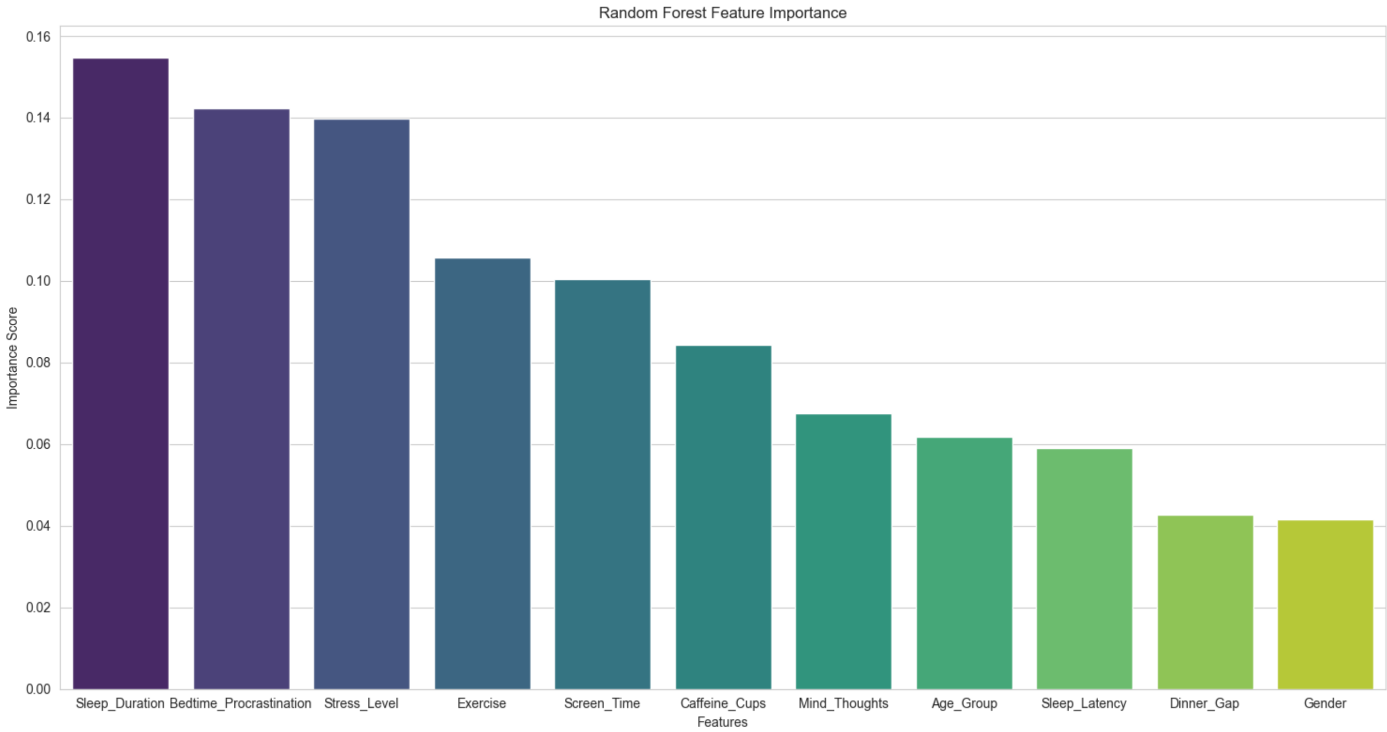

Figure 4: Feature Importance of Random Forest Classifier Model.

4.3 ROC-AUC Comparison

An ROC curve comparison visually confirmed the trade-off between sensitivity and specificity:

- **Random Forest** achieved the highest AUC of 0.88.
- **Gaussian Naive Bayes** achieved an AUC of 0.86, outperforming SVM (AUC = 0.83) in ranking capability, despite having lower overall accuracy.

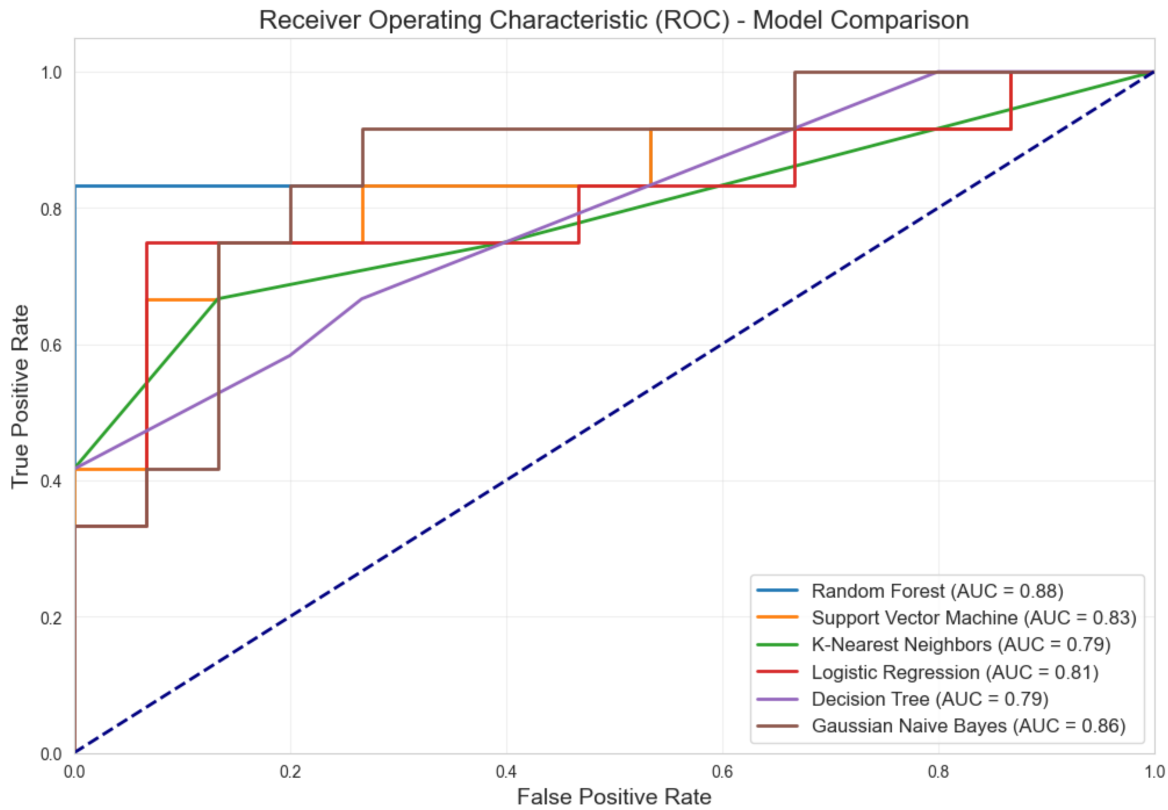

Figure 5: ROC Curve comparison among different models.

4.4 Addressing Research Gaps

This study successfully bridges specific gaps identified in the literature:

- **Algorithmic Diversity:** Unlike single-model studies, our comparative analysis proved that Random Forest (an ensemble method) strictly outperforms linear models (Logistic Regression) for lifestyle data, confirming the non-linear nature of sleep habits proposed by Bhatti et al. (2025).
- **Validation Rigour:** To address validation concerns in smaller studies, the implementation of our custom "Overfitting Gap" logic ensured that the reported accuracy is robust. For Random Forest, the gap between training (95.00%) and testing (85.19%) was within acceptable limits (<15%), confirming generalisability.
- **Integration of Psychological Nuances:** Standard datasets often rely heavily on physical metrics like BMI or Step Counts. However, these metrics miss the psychological triggers of sleep loss. Our study fills this gap by explicitly modelling behavioural variables like "Bedtime Procrastination". The high feature importance of this variable (in Random Forest) validates that predictive models must move beyond physical health metrics to include psychological behavioural patterns for modern populations.

5. CONCLUSION AND FUTURE SCOPE

This project successfully developed a machine learning framework to predict sleep quality from lifestyle habits. The comparative analysis identified Random Forest as the superior algorithm, achieving an accuracy of 85.19% and an ROC-AUC of 0.88. A key strength of this study lies in its demographic inclusivity. Unlike research limited to specific student cohorts, this study validated its findings using survey responses covering a comprehensive age range. This wide distribution confirms that behavioural factors specifically Sleep Duration, Bedtime Procrastination and Stress Level are the dominant predictors of sleep quality across the general population, often outweighing simple stress metrics regardless of the user's age group. The implementation of a strict "Overfitting Gap" validation logic further ensures that these findings are robust, generalisable, and not a result of training data bias.

Future Scope:

- **Wearable Integration:** Integrating real-time data from smartwatches (Heart Rate, SpO2) could validate the self-reported survey data with objective physiological markers.
- **Mobile Application:** The model can be deployed as a mobile app to provide users with a daily "Sleep Score" and personalised recommendations (e.g., "Reduce screen time by 30 mins").
- **Longitudinal Study:** Tracking users over months would allow the model to learn from changing habits rather than a static snapshot, enabling the detection of long-term sleep trends.

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A Study on the technological architecture, strategic integration, and implications for the digital economy of e-commerce and digital marketing technologies

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Abstract

The international territory of corporate arrangements and promotion communication has been drastically changed by the fast development of digital structure, the journey generality of movable connectivity, the objection of artificial intelligence and the use of big data analytics, these days, digital marketing technology, and e-commerce platforms work together to produce ecosystem that functions effectively and allows for data driven decision And allow for real-time communication between companies and the guest further to impacting consumer involvement and purchasing the integrated digital platforms also have an impact on organisational behaviour, performance, effectiveness, competitive and inventions. The study offers through research of the technological theoretical and latest development of this system, it is supported by secondary data, showing the useful results, the ethical use of client data government reports, AI driven marketing strategies and compliances and the operations of cyber security increasingly complex. Digital surroundings are the challenges for digital marketing and e-commerce. This paper 6 to give a comprehensive understanding on businesses that useful for digital technologies and sustainable growth for both the advantages and disadvantages.

Keywords: E-commerce, Digital marketing technologies, Artificial intelligence, Big data analytics, Omnichannel strategy, Digital transformation

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1. Introduction

1.1 Conceptual Foundations

The term of e-commerce defines the practice of showing commercial over automation networks, mainly the Internet. It also includes the platform waste digital models, consumer to consumer B2B and B2C models, digital tool, automation platforms and algorithm intra that facilitate the online advertising and performance optimisation are all included in the category of digital marketing, it also have come together to create the highly integrated digital ecosystem where supply chain operations and data analytics and customer engagement all happen in real time. Quick advances in technology have given better businesses that can use data as a strategic management for a competitive age.

1.2 Statement of problem: Effective integration, strategic alignment and long-term value generation are the major problem in digital marketing and e-commerce technologies. Despite the significant performance benefit, benefits of technology, big data analytics and marketing automation. There are limited digital capabilities and complex regulatory rules and regulations. Thus, the customer privacy and data security, dependent on algorithm driven marketing that is digital marketing.

Therefore, through analytical framework, the strategic integration of digital marketing and e-commerce technologies to improve organisational performance while tackling operational, ethical and legal issues are required so that this paper aims to close this gap by offering an organised knowledge of digital commerce ecosystem.

1.3 Objectives of the Chapter

- The objectives of this study are:
- To examine the historical evaluation of e-commerce and digital marketing technologies
- To analyse theoretical frameworks, explaining technologies, adoption, and competitive
- To evaluate the technological architecture, supporting modern e-commerce
- To assess the impact of digital integration on organisational performances
- To investigate consumer behaviour in digital context with respect to trust privacy and personalisation.

1.4. Background and Theoretical Framework

1.4.1 Evolution of E-Commerce

E-commerce began with Electronic Data Interchange technologies, which made it possible for businesses to communicate in an organized manner. The commercialization of the internet in the 1990s led to the emergence of digital marketplaces and online shopping platforms. Secure encryption technologies increased transaction reliability and customer trust.

Subsequent innovations introduced platform-based business models with multi-sided markets and network effects. Mobile commerce, which enabled transactions through digital wallets and cellphones, further expanded accessibility. These technological advancements significantly reduced transaction costs and increased global market participation.

1.4.2. Evolution of Digital Marketing Technologies

Initially, the cornerstones of digital marketing were static websites and banner ads. As search engine algorithms have improved, search engine marketing and optimization have emerged as crucial instruments for increasing online visibility. The rise of social media platforms, which enabled peer influence and instantaneous consumer interaction, made participatory marketing feasible.

The integration of customer relationship management systems and marketing automation platforms marked the beginning of the transition to data-driven interaction. Artificial intelligence and machine learning technologies have enabled chatbot-driven communication, sentiment analysis, recommendation engines, and predictive analytics, which enhance operational efficiency and personalization.

2. Literature Review:

Perceived utility and perceived ease of use impact adoption behavior, as explained by the Technology Acceptance Model (Davis, 1989). According to Rogers (2003), the diffusion of innovation theory explains how new technologies proliferate throughout social systems. In order to maintain competitive advantage, the Resource-Based View highlights the strategic significance of unique and valuable digital assets (Barney, 1991). According to Teece (2018), dynamic capability theory emphasizes the significance of ongoing adaptation in quickly changing technological environments.

Studies on the development of e-commerce highlight how it can lower transaction costs, improve market accessibility, and ease international trade. According to early research, the commercialization of the internet and the creation of electronic data interchange systems were significant turning points in the expansion of digital commerce (Laudon & Traver, 2022; Chaffey & Ellis-Chadwick, 2019).

Digital marketing technologies, including artificial intelligence, marketing automation, and big data analytics, have been shown to significantly improve customer personalization and engagement. According to studies, these tools help businesses make data-driven decisions that improve operational efficiency, boost conversion rates, and optimize marketing campaigns (Wedel & Kannan, 2016; Verhoef, Kannan & Inman, 2015).

How people and organizations adopt digital technologies is explained by theoretical frameworks like the Diffusion of Innovation Theory and the Technology Acceptance Model (TAM). While Rogers' (2003) theory emphasizes the role of early adopters in technology acceptance and the diffusion of innovation through social systems, TAM emphasizes perceived usefulness and ease of use as important determinants of adoption (Davis, 1989).

According to strategic management viewpoints, especially the Resource-Based View and dynamic capabilities theory, digital capabilities are rare, valuable, and unique resources that offer long-term competitive advantage. Businesses are better equipped to react to shifts in the market and technological disruptions when they have sophisticated analytics infrastructure, proprietary algorithms, and talented digital personnel (Barney, 1991; Teece, 2018).

Trust, privacy, and personalization are important factors that influence online engagement, according to consumer behavior research in digital commerce. Research indicates that while excessive personalization may raise privacy concerns, safe payment methods, clear privacy policies, and reliable customer reviews all have a positive impact on purchase intention (Chaffey & Ellis-Chadwick, 2019; Wedel & Kannan, 2016).

The ethical, legal, and governance ramifications of data-driven marketing are also examined in recent research. To preserve customer trust and long-term engagement, researchers stress the significance of algorithmic transparency, responsible AI deployment, and adherence to data protection regulations (Verhoef, Kannan & Inman, 2015; Wedel & Kannan, 2016).

3. Research Methodology:

In an effort to provide theoretical integration, empirical support, and analytical insights, this chapter adopts a rigorous and systematic approach. To ensure triangulation, validity, and comprehensive interpretation of findings related to e-commerce and online marketing technologies, the method combines quantitative and qualitative approaches.

3.1 Research Design

The research employs a mixed-method research methodology that involves both qualitative and quantitative analysis. The complexity of digital commerce environments, which require both measurable performance criteria and interpretation, forms the basis for the justification of the research methodology.

Investigating the relationships between organizational performance outcomes and the level of technology adoption is the primary objective of the quantitative research methodology. This research methodology enables the researcher to statistically analyze the relationships between variables such as revenue growth, customer engagement metrics, and levels of personalization.

The qualitative aspect explores procedures of transformation within organizations, management perspectives, and challenges of implementing strategies. This aspect introduces complexity to quantitative data by means of interpretation.

Within the sequential explanatory framework of research design, qualitative evidence is applied to interpret quantitative findings. This approach reduces bias in methodology and enhances validity.

3.2 Research Approach

Employing a deductive research approach, the research utilizes popular theoretical frameworks like the Resource-Based View, Diffusion of Innovation Theory, Technology Acceptance Model, and Dynamic Capability Theory. These theories form the basis of intellectual constructs that propose hypothetical relationships between the integration of digital technology and performance outcomes, which are later tested using real data from previous studies.

On the other hand, the analysis of themes in qualitative data employs elements of inductive research. Without setting any boundaries, patterns emerging from governance barriers, ethical concerns, and implementation challenges are identified.

3.3 Data Sources

3.3.1 Secondary Data

The sources of secondary data include global digital commerce statistics, industry reports, business case studies, and peer-reviewed scholarly journals. Scholarly databases were used to find empirical studies that investigated the relationship between the adoption of digital technology and firm performance.

Industry reports contain compiled data on trends in marketing automation, cybersecurity incidents, the adoption rate of AI, and the growth of mobile commerce. Secondary data was used to validate key findings and ensure that it is consistent with broader industry trends.

3.4 Sampling Technique

Purposive sampling was employed in the quantitative study to select respondents who actively engaged in online purchasing. This ensured that the participants possessed experience with digital commerce platforms.

Criterion-based sampling was employed in the qualitative study to select professionals who were directly involved in the implementation of digital strategies. The participants' managerial roles, industry experience, and involvement in digital transformation projects were considered when selecting participants for the study.

The combination of purposive and criteria sampling enhanced the reliability and relevance of the data collected.

3.5 Variables and Measurement

The research study focuses on various important variables, which are classified into independent, dependent, and moderating variables.

The main independent variable is the intensity of digital technology integration, which is measured by the adoption of AI, automation, omnichannel integration, and analytics capability development.

The dependent variables are the levels of customer engagement, conversion rates, revenue, efficiency, and customer retention.

The moderating variables are consumer trust, privacy protection, and technological literacy.

The measurement scales used in the research study were taken from the previous research studies on digital marketing and information systems. The reliability of the measurement scales was calculated by internal consistency, and construct validity was calculated by theoretical alignment.

3.6 Data Analysis Techniques

Thematic analysis was employed to analyze the qualitative data. To identify recurring themes related to strategy alignment, governance challenges, cybersecurity risks, and the evolution of digital competencies, the transcripts were coded. To identify frequent implementation challenges and best practices, the themes were explored.

To integrate the quantitative and qualitative data, triangulation was employed. To identify differences in the data, divergent data was analyzed in depth to establish contextual differences, and to support the analysis, convergent patterns were reinforced.

3.7 Reliability and Validity

By following established theoretical models, the construct validity was maintained. External validity was enhanced by using data triangulation from multiple sources. The overall methodological rigor was enhanced and the risk of single-source bias was reduced by employing a mixed-methodology approach.

3.8 Limitations of the Methodology

It is important to acknowledge some limitations despite the use of rigorous methodology. The generalizability of the findings may be constrained by the use of purposive sampling across all industries. The rapid pace of technological evolution may render some findings industry-specific. Response bias may be introduced by using self-reported survey data. In addition, secondary data may not capture the nuances of the subtleties at the firm level but rather the broader industry trends.

Future research may employ an experimental approach to better capture the causal relationships and longitudinal research designs to assess long-term performance effects.

4. Results

Based on empirical studies, customization solutions are proven to significantly improve client retention and conversion rates. The efficacy of dynamic pricing and the accuracy of segmentation are improved by artificial intelligence. The supply chain coordination and demand forecasting are improved by big data analytics. While algorithm dependence introduces instability, social media analytics have a positive relationship with customer loyalty and business awareness. With the aid of privacy policies and cybersecurity guidelines, consumer trust is an essential determinant of purchase intention. Thanks to digital payment solutions and improved user interface design, mobile commerce continues to develop.

4.1. Findings (Secondary Data Analysis)

- Mobile commerce and online marketplaces are the key drivers of the 15% annual growth rate in e-commerce transactions.
- For client segmentation, most large companies use marketing automation tools and AI-powered recommendation systems.
- Click-through rates, session times, and repeat business are all improved by digital marketing tools.
- Automation and predictive analytics reduce logistical costs and reduce the risk of stockouts.
- Compliance with data protection regulations and secure payment options improve client loyalty and trust.
- Voice commerce, omnichannel, and AR/VR marketing are new trends that seek to enhance the client experience.
- High investment barriers, lack of qualified personnel, and compatibility challenges are barriers to adoption.

5. Discussion

Cross-functional coordination between marketing, operations, and information systems is necessary for the strategic integration of e-commerce and digital marketing technologies. Digital capabilities serve as strategic assets that improve the capacity for innovation and agility. However, strong regulatory compliance and open governance frameworks are required due to ethical issues about algorithmic bias, privacy, and data governance. To reduce implementation risks, organizations need to make investments in cybersecurity systems, scalable infrastructure, and digital literacy training. Standards for consumer protection and incentives for innovation must be balanced by policymakers.

Blockchain and other emerging technologies promise improved transactional transparency. Experiential commerce is being redefined by augmented and virtual reality technology. Conversational AI and voice-enabled search are changing how consumers interact with brands. Digital supply chain optimization and ethical marketing strategies are being impacted by sustainability factors.

Future studies should examine the effects of AI adoption on performance over time, cultural variations in views of digital trust, and governance mechanisms for the application of moral algorithms.

7. Conclusion

Digital marketing and e-commerce technology are the cornerstones of the modern digital economy. Global scalability, operational efficiency, and personalized engagement are made possible by their integration. However, regulatory compliance, ethical governance, and strategic alignment are necessary for sustained growth. Navigating the changing world of digital commerce requires a thorough awareness of the technological, behavioral, and strategic aspects.

In conclusion, by enabling highly integrated, data-driven, and customer-centric ecosystems, the convergence of e-commerce and digital marketing technologies has completely changed the dynamics of contemporary business. Businesses can achieve improved operational efficiency, increased customer engagement, and a lasting competitive edge by utilizing digital infrastructure, artificial intelligence, big data analytics, and mobile connectivity. However, there are drawbacks to the quick speed of technological advancement, such as the necessity for strong governance frameworks, privacy issues, cybersecurity threats, and moral conundrums.

This chapter shows that optimizing the advantages of digital transformation requires a strategic alignment between organizational goals and technology adoption. In the future, new technologies like voice commerce, blockchain, augmented and virtual reality, and predictive analytics have the potential to drastically alter the digital commerce environment. Businesses will be best positioned to prosper in a global economy that is becoming more linked and data-driven if they proactively embrace innovation, invest in digital capabilities, and adhere to ethical and regulatory norms.

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INFLUENCE OF SOCIAL MEDIA ON KOREAN FOOD TRENDS AMONG GEN Z IN MUMBAI

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ABSTRACT

The global rise of the Korean Wave (Hallyu) has significantly increased the visibility of Korean cuisine through digital platforms; however, its influence on young consumers in the Indian context remains underexplored. This study investigates how social media influences Korean food trends among Gen Z in Mumbai. The research aimed to examine the role of social media in shaping awareness and popularity of Korean food, explore the influence of food content on Gen Z's decision to try Korean food, and assess the cultural associations driving consumption patterns. A mixed method was employed, including surveys of 100 respondents, structured interviews with three café managers, content analysis of 170 Instagram posts, and 50 Zomato reviews. Findings indicate that while 88% of respondents have tried Korean food at least once, only 22% consume it regularly. Instagram emerged as the dominant platform, with 79% of respondents acknowledging its role in enhancing desirability. Peer influence (71%) and viral food trends (55%) were more impactful than traditional influencer marketing. Café insights revealed that 20–50% of customer visits were driven by online exposure. Content analysis showed a strong preference for reels (82%), with nearly half incorporating cultural elements such as K-pop and K-dramas. Zomato reviews highlighted authenticity (76%) and ambience or "Instagrammability" (46%) as key drivers, while affordability remained a constraint. The study concludes that social media plays a significant role in shaping awareness and desirability of Korean cuisine among Gen Z in Mumbai, though sustained consumption depends on pricing and continued innovation.

Keywords: Gen Z, Korean Wave (Hallyu), Korean Cuisine, Korean Food Trends, Social Media Influence, Consumer Behaviour, Instagram Marketing, Food Reels, Influencer Marketing, Cross-Cultural Consumption, Food Trends in Mumbai.

1.INTRODUCTION

“La destinée des nations dépend de la manière dont elles se nourrissent.”
(“The fate of nations depends on the way they eat.”)
(Brillat-Savarin, 1970)

Food is seen not merely as nourishment but also as a cultural ambassador, promoting cross-cultural appreciation, transnational connections and enhancing global familiarity.

Korean cuisine has evolved into a powerful tool of soft power, benefiting from the global popularity of the Korean Wave, also called ‘Hallyu’, which is a significant cultural phenomenon viewed by its worldwide domination and fame spotlighted with the rise of K-pop, K-dramas, K-fashion, K-beauty trends and the Korean language.

Korean cuisine focuses on fermented foods like kimchi and doenjang, along with balanced meals such as bibimbap and nutrient-rich soups. As health becomes a major global concern, Korean food stands tall for marrying flavour with function, offering both taste and nutritional value.

From Korean BBQ to hotpots, the emphasis on communal dining and shared meals has redefined eating as a social ritual. Millennials and Generation Z resonate with this trend, who value shared experiences.

Mukbang culture (a South Korean trend where individuals live-stream themselves eating large quantities of food while engaging with their viewers) and social media trends further amplify Korean food’s visibility and desirability. These enhance online interaction, challenge participation, and community building around Korean dishes.

Korean food’s success not only lies in its authenticity but also in its adaptability. Chefs across the world incorporate Korean flavours into fusion dishes and also offer dishes that are plant-based and suit the local palates.

Korean food is not just a trend; it is a global cultural movement. It thrives on the intersection of media, health, identity and innovation.

The researchers are interested in studying the influence of social media on the popularity and consumption of Korean food trends among Indian Gen Z using a mixed-methods approach that includes surveys, in-depth interviews, and content analysis. This literature review explores existing studies on social media-driven food culture, the impact of the Hallyu wave, and youth consumer behaviour to provide a foundation for the research.

2. SIGNIFICANCE

This study is highly significant as it examines the intersection of the rising influence of social media, the phenomenon of cultural exchange through globalisation, and consumer behaviour among the youth. In recent years, Korean culture has witnessed a massive surge in popularity worldwide, including in India. This trend, among Gen Z, is largely fuelled by social media platforms.

The phenomenon of cultural exchange is not merely limited to food; it examines the deeper nuances of shifts in how we interact with culture, its impact on identity as a global citizen, and global trend adoption.

This study would contribute significantly to understanding cultural globalisation through food. Food is one of the primary pillars of a culture, and Korean food has become a hallmark symbol of the larger Korean wave (Hallyu) that has been widely embraced. It would also offer insights into the transformative role that social media plays in shaping food preferences and consumer behaviour. Through studying and deeply examining how Indian Gen Z consumes and interacts with content, the research would reveal how social media not only becomes a driving force but also facilitates the localisation, discovery, popularity, and desirability of foreign food trends.

By exploring these facets, the study would be able to add valuable contributions to the branches of globalisation studies, consumer behaviour, food culture, and media studies.

3. RELEVANCE

This topic is highly relevant due to the presence of the K-factor in pop culture globally. From food, fashion and skincare, every lifestyle trend begins with a 'K'. From making dalgona coffee at home in the 2020 COVID-19 lockdown era to binge-watching the final episodes of Squid Game Season 3 on Netflix in 2025, the Hallyu wave has grown year by year. 2025 has already seen Korean artists (Jackson Wang and Wave To Earth) visit India for their concerts and promotions, paired with the rise of Korean cafés and their experiential Korean barbecue.

Social media is one of the major contributors to the rise of the K-wave in India. Platforms like YouTube, Instagram, X (formerly Twitter), Weverse, etc., have now made Korean content more accessible to fans, increasing conversations and connections with the Korean culture online as a sense of belonging and comfort. The K-wave also proved to be a new cultural product for streaming platforms. Netflix, in a survey, found that over 60% of its members have watched Korean titles in 2023 alone. At the same time, Prime Video by Amazon also largely increased Korean content options on its platform (Korea Centre, 2025).

This rise of Korean content on OTT has reflected on the content on social media, the Gen Z playground, which shapes their opinions, preferences and exposure to international cultures. Reels, Mukbang and ASMR eating videos, and influencer posts have become the driving force behind adapting Korean cuisine among the urban Indian Gen Z, who are digital-first and consume large volumes of content daily. Korean food products are taking over every shelf in Indian supermarkets, while Korean-inspired cafés and restaurants are booming across the country's metropolitan areas. Online presence has become a crucial aspect for establishments trying to enter the Korean market. Understanding how social media influences these food choices is highly relevant in today's times for marketers, cultural researchers, and businesses aiming to succeed in the expanding Korean food space in India. More broadly, the study highlights how digital platforms are transforming Indian Gen Z in terms of consumer behaviour, developing tastes and adapting to cultural practices in a globalised market.

4. LITERATURE REVIEW

From being a comfort cuisine in South Korea to becoming a global cultural crown, Korean food has grown into much more than just food on shelves in Korean convenience stores. With the rise of Hallyu and digitalisation, food has become a way to connect, express and explore cultures, especially for Gen Zs who thrive online. This literature review aims to explore and bring together the symbolic power of food, the influence of the Korean Wave, and the way digital media shapes cultural exchange. It covers multiple themes like the emotional and aspirational appeal of Korean food, its role as a soft power tool, the rise of influencers and food bloggers, and how platforms like TikTok and Instagram create and sustain food trends.

4.1 FOOD: A SYMBOLIC AND CULTURAL MEANS

Food is a constant and shared element in human societies throughout history. It creates a deeper symbolic and cultural meaning while essentially being important for survival.

Food is a "nonverbal means of sharing meanings" in which everyday choices, such as who eats first or how food is served, reflect deeper cultural structures. We're moving further from recognising food as a source of nourishment to a "main factor in how we view ourselves and others". Food is essentially a medium through which we express ourselves. Food practices help people navigate their identity in a world that is increasingly global, commercial, and image-conscious.

The increasing popularity of food-related media, from celebrity chef shows to Instagram, demonstrates how food has become a performative spectacle. What we eat is now part of how we brand ourselves, consume culture, and share identity online.

Food is no longer merely functional; it is curated, photographed, and ritualised for public display. This reflects how food has entered the domain of mass communication, creating a cultural feedback loop between audience, identity, and meaning (Stajcic, 2013).

Figure 1.1 Courtesy Image: Guillaume Belvèze for Le Monde

4.2 FOOD AS SOFT POWER

A country's culture, political values, and foreign policies make up for its soft power. When others admire a country's values, culture, or policies, they are more likely to align with their interests voluntarily. In contrast to hard power, which involves the use of military force or economic incentives.

Food as a vehicle of soft power carries symbolic and cultural meanings that can communicate ideologies and values from one society to another. Soft food power operates on three levels: Cultural Propaganda – exposure and adoption of foreign foods; Democratic Change – shifts in public values leading to policy influence; and Systemic Change – deep integration of foreign food values into national systems. Food's power lies not in the food itself but in its cultural-symbolic associations (Reynolds, 2012).

4.3 HELLO HALLYU, THE KOREAN WAVE

Figure 1.2 Images: Shutterstock

By the late 1990s, Korea had established itself as a key player in transnational popular culture, exporting its media products to various Asian countries, including Japan, China, Hong Kong, Taiwan, and Singapore. The global rise of Korean culture became known as the Korean Wave or "Hallyu" — a term that refers to the rapid surge in popularity and enthusiasm for Korean cultural exports such as K-pop, films, fashion, cosmetics, cuisine, and lifestyle.

The Korean culture industry was developed for socio-economic, cultural and political reasons in the late 1990s. In the wake of the 1997 Asian financial crisis, the Korean government started funding television and film production, subsidising music companies and negotiating trade deals to lower barriers for Korean media abroad. This turned "Hallyu" into a pillar of national economic policy, helping cultural hits generate billions of dollars and boosting Korea's visibility worldwide.

In the past, most of the world watched Western (especially American) shows and listened to Western music. But now, Korean media is also being watched and loved in the West. This is called a "contra-flow", where culture flows both ways. Korean dramas often use Hollywood-style storytelling, and K-pop mixes in Western music styles. Western artists are now teaming up with Korean stars. This give-and-take is changing who influences global entertainment.

Devoted fans around the world have posted on social media, helping Korean content spread virally online, making new shows and songs reach international audiences instantly (Kim, 2013).

4.4 DIGITAL PLATFORMS AND CULTURAL EXCHANGE

Digital platforms like social media, discussion forums and virtual groups are powerful tools that connect people across borders, encouraging cultural interaction and exchange, collaboration and understanding. These platforms allow individuals to explore and share diverse cultural expressions, such as literature, art, music, and food, worldwide.

Asia is home to immense cultural diversity, and with the rise of rapid globalisation and digital innovation, it has become a vital landscape for cross-cultural exchange via technology. Social media platforms have become informal cultural hubs with audiences sharing and discussing customs, traditions and everyday practices. Platforms like YouTube and Netflix help globalise Asian content (e.g., Korean dramas, Japanese anime) by localising it through subtitles and dubbing.

The transformative power of online communities goes beyond casual interaction. They represent the microcosms of global society, where shared interests create a space for cultural blending, idea exchange and collaboration. Digital platforms become tools for global connection, cultural sustainability, and social innovation. (Banerjee et al., 2019).

4.5 KOREAN CULTURE AND MEDIA

For many countries, especially those seeking to enhance their global image, the media has become a powerful tool of soft power, a way to cultivate cultural appeal and influence international audiences without coercion.

Among the countries that have successfully leveraged media for global recognition, the Republic of Korea, commonly known as South Korea, stands out as a prime example. Traditionally known for its technological prowess, shipbuilding, robust economy, and some of the fastest internet speeds in the world, Korea has now become globally synonymous with a cultural phenomenon called the Korean Wave or Hallyu. This cultural movement encompasses the worldwide appeal of Korean pop music, television series, movies, skincare and beauty trends, fashion, and culinary traditions.

Initially aimed at boosting South Korea’s influence in East and Southeast Asia, the Korean Wave has grown to captivate audiences throughout the Americas, Europe, the Middle East, and other regions worldwide. It represents more than just entertainment; it offers a dreamlike world of aesthetic perfection, emotional depth, and rich cultural values. Through carefully curated media content, Korea exports not only products but also human values, ideologies, and a way of life that deeply resonates with global audiences. This has contributed significantly to Korea’s cultural diplomacy, national branding, and economic growth.

Figure 1.3 Psy's "Gangnam Style" Courtesy Photo

A landmark moment in the globalisation of Korean pop culture was the 2012 viral hit "Gangnam Style" by PSY. Though rooted in localised satire about the wealthy Gangnam district in Seoul, the song gained explosive international attention thanks to platforms like YouTube, where it became the first video to reach one billion views.

One of the defining characteristics of Hallyu is its ability to evolve. The so-called "Second Wave" of Korean pop culture, driven by the global rise of K-pop groups like BTS, EXO, and BLACKPINK, is a testament to its adaptability. South Korea's rise as a cultural powerhouse is driven by creativity and widespread digital access (Anand & Baek, 2024).

4.6 KOREAN FOOD AS THE RISING STAR OF HALLYU

Figure 1.4 Image Source: allkpop

The Hallyu wave, born as an influence of K-drama and social media, has resulted in over 600 Korean enterprises operating in India, both small and large, and also establishments that offer Korean food, many at several locations across India. K-dramas are not just pure entertainment but also shape aspirations among viewers. Viewers get curious about the stories, fashion, and especially the food shown on screen. This has caused a significant increase in demand for Korean foods such as kimchi, ramen, and soju in Indian markets, leading to record-high exports. Social media has played a huge role in this shift, with platforms like Instagram filled with Korean drama fan pages, Mukbang challenges, influencer posts and food content. The trend took over the internet massively during the 2020 COVID pandemic. Interestingly, the study found that the influence of K-culture, including food, is consistent across different age groups, genders, and education levels. This hints that trends and food preferences driven by social media are widely embraced among Indian Gen Z, regardless of background (Naidu et al., 2023).

4.7 KOREAN FOOD: AN AFFORDABLE CULTURAL PRODUCT

Many fans cannot afford K-pop merchandise because of the high import costs and customs fees. Korean food has replaced K-pop merch as a more affordable way to engage with Korean culture. K-dramas often show characters eating gimbap, japchae, tteokbokki, and kimchi fried rice, and as viewers watch, they learn how to make and consume these foods as well. This, with the rising number of Korean cafés and Indian supermarkets that are now carrying more Korean ingredients, has made Korean food more common in Indian homes. Korean food is not just about the taste for many; it’s about feeling the emotional bond that has been developed around experiencing Korea (Biswas & Roy, 2023).

4.8 GLOCALISATION AND THE ASPIRATIONAL APPEAL BEHIND K-CULTURE

The rising popularity of Korean food among the Indian Gen Z stems from a form of glocalisation, as described by sociologist Jan Pieterse (1994) as “structural hybridisation” in globalisation, where “people assert local loyalties but want to share global values and lifestyles”. South Asia (India) offers “fertile soil for K-pop and K-dramas to flourish due to its relatively young generation and growing internet and smartphone penetration rate” (Gosh, 2002). It further boosted this hybridisation, especially in metro cities like Kolkata, where Korean cafés offer not just food but an experience of the Hallyu wave itself because Korean food lovers are not just in it for the foodie factor but also enjoy the Korean entertainment culture and are keen to learn Korean table etiquette as well as the language for their aspiration to visit South Korea.

4.9 THE POWER AND SUBTLETY OF INFLUENCER MARKETING ON SOCIAL MEDIA

Brands are getting smarter with how they sell food and drinks on social media. Influencers play a huge role, especially those who seem relatable and trustworthy. People are more likely to notice and remember ads when influencers include personal stories or make the product part of their everyday life. Emotional content tends to grab more attention than plain product shots.

Even the way a post looks, colours, captions and hashtags make a difference (Afandi & Marsasi, 2023).

4.10 TIKTOK TAKES OVER GEN Z'S FOOD CHOICES

TikTok creators and influencers affect the food-buying decisions of Gen Z and play a huge role in the food choices of the youngsters right now. It finds these 3 traits - communication skills, trustworthiness and attractiveness strongly affect whether Gen Z are likely to buy the food products advertised. When influencers seem loyal and confident in the product they are promoting, look appealing and are genuine, their followers are more likely to trust and follow their suggestions. It builds a clear framework, compiling these qualities/traits to explain how purchase intentions are shaped (Radhi et al., 2024).

4.11 RESTAURANT MARKETING IN THE YOUNG DIGITAL SPACE

Social media has emerged as the primary marketing medium in the food and restaurant industry. Facebook, Instagram, Zomato, and X (formerly Twitter) are being used not only to advertise but also to engage directly with consumers. Zomato, being the most effective platform for discovering restaurants, and consistent campaigns, promos, and influencer engagement, increased customer footfall, especially among tech-savvy consumers. Gen Z consumers today actively seek out popular content and real experiences, and social media has made it possible to target them through campaign-based visibility, personalised feedback loops, and trust-building (Deshwal et al., 2018).

4.12 SOCIAL MEDIA INFLUENCE AND DINE-OUT CULTURE

Figure 1.5 Courtesy Image: James Tran

Social media has a big impact on what people buy because they are constantly seeing trends, influencers, and content made by their peers. About 74% of young Indian consumers use social media to decide what to buy, looking at reviews and seeing what other people have to say about products instead of traditional brand messages (Bharucha, 2018).

Millennials are using Instagram as their new restaurant guide. For them, it is not only about food quality or word-of-mouth, but also about how the experience looks online. They often avoid places with an unimpressive Instagram presence and rely on geotags, hashtags, and restaurant profiles before dining, making Instagram a visual menu and brand identity. To meet these expectations, restaurants design their interiors and presentations to be photo-worthy. As a result, user-generated posts act as free marketing, reinforcing Instagram as a form of social proof (Tobin, 2017).

In today's digital age, dining is not just about food but also about experiences, visuals, and sharing. It has become a form of self-expression and social identity, where influencer content and user-generated media shape consumer choices. Consumers actively share their experiences to recommend or critique restaurants, helping others make informed decisions. They rely on likes, shares, and reviews as social proof, while also selectively interpreting content based on personal preferences (Kesa & Koufie, 2020).

Sharing experiences online has become second nature for Millennials and Gen Z, driven by self-expression, social recognition, and the desire to document moments. Factors such as food quality, service, atmosphere, and cultural authenticity influence this behaviour. Gen Z, in particular, frequently shares real-time content, while Millennials show a stronger link between sharing and loyalty, making them more likely to revisit or recommend restaurants (Poyoi et al., 2024).

4.13 WHY GEN Z IN BANGKOK ARE DRAWN TOWARDS KOREAN FOOD CHAINS

The decision to eat K-food isn't random but rather is influenced by how easily accessible and affordable it is, along with how much they enjoy it. This idea, called "perceived behavioural control" (a person's belief about how easy or difficult it is to perform a specific behaviour), turned out to be the biggest factor in shaping their intention to eat at Korean franchises. It shows how much the Korean Wave has impacted young Thai consumers' food choices (Siripiyaphat, 2023).

4.14 GANJANG GEJANG: FOOD CREATIVITY AND SOCIAL MEDIA MARKETING IN INDONESIA

Social media and new product ideas have influenced people's love for a Korean dish called Ganjang Gejang, made by a brand called Daebag.e in Indonesia. The thing that stood out the most was that creativity in food and social media marketing didn't just boost sales, but it also made customers happier overall. What people see online, and the uniqueness of the product, go hand in hand in shaping loyalty (Dumatubun & Tambunan, 2025).

The researchers are interested in studying the influence of social media on Korean food trends among Indian Gen Z using a mixed methodology of surveys, in-depth interviews and content analysis.

Overall, the literature highlights the growing role of Hallyu in shaping global cultural consumption, the increasing importance of social media in influencing food preferences, and the use of food as a medium of cultural expression and soft power. However, these studies are often examined in isolation. There is limited research that integrates these perspectives to understand how Korean food trends are constructed and experienced within specific urban contexts, particularly among Gen Z in India.

5. RESEARCH GAPS

Overall, the literature establishes three key gaps:

1. Food functions as a symbolic and soft power tool in global cultural exchange.
2. Hallyu has expanded beyond media into everyday lifestyle practices, including food.
3. Social media plays a central role in shaping contemporary food consumption patterns.

Existing studies remain fragmented across these domains, with limited research integrating soft power, Hallyu, and digital media influence to examine how Korean food trends are constructed and consumed in specific urban contexts.

While global and regional studies provide valuable insights, there is a lack of city-level, India-specific research, particularly on Gen Z consumers and their everyday interactions with Korean food on social media platforms. These studies conclude that the Korean wave, through celebrity endorsements, country-of-origin image, cultural values, and uniqueness, positively affects consumers' purchase intentions, positioning Korean cuisine as a powerful tool of soft power and a broader cultural movement.

The Korean wave has recently witnessed a massive surge in popularity in India, especially among Gen Z, largely fuelled by social media platforms, with the trend accelerating during the 2020 COVID pandemic. This highlights the need to understand the diverse purchasing patterns of Indian consumers with respect to Korean products and to assess the growth potential of Korean cuisine in India. While existing studies address the broader influence of K-culture, they often lack specific city-level insights and a focused examination of everyday food consumption trends driven by social media in metropolitan contexts such as Mumbai. This paper addresses these gaps by exploring the following research question.

6. RESEARCH QUESTION

How does social media influence Korean food trends among Gen Z in Mumbai?

7. RESEARCH OBJECTIVES

1. To examine the role of social media in shaping the popularity and consumption of Korean food among Gen Z in Mumbai, India.
2. To explore the relationship between influencer content and Gen Z's interest in trying Korean food in Mumbai.
3. To assess the impact of social media platforms on increasing awareness and desirability of Korean food trends among Gen Z in Mumbai.
4. To understand how online engagement affects Korean food choices and dining behaviour among Gen Z in Mumbai.
5. To explore how Korean restaurants and cafés in Mumbai perceive the impact of their social media content on consumer footfall and engagement.

8. RESEARCH HYPOTHESIS

H1: Increased exposure to Korean food content on social media positively influences Gen Z's intention to try Korean food in Mumbai.

H2: Influencer marketing on platforms like Instagram has a significant positive impact on Korean food consumption among Gen Z in Mumbai.

H3: The more frequently Gen Z in Mumbai interacts with Korean food content online, the greater their likelihood of dining at Korean restaurants.

9. RESEARCH METHODOLOGY

9.1 Research Design

This study uses a mixed-method approach to explore how social media influences Korean food trends among Gen Z in Mumbai. Both qualitative (survey) and quantitative (interviews and content analysis) methods were used to gain comprehensive insights into consumer behaviour and market perspectives. Data triangulation across surveys, interviews, and content analysis was used to strengthen the credibility of findings.

9.2 Data Collection

9.2.1. Primary Data:

- **Surveys:** A structured questionnaire was administered to 100 Gen Z respondents (aged 18–25) residing in Mumbai. The questionnaire consisted of a combination of Likert-scale and multiple-choice questions designed to assess social media usage patterns, exposure to Korean food-related content, and its influence on consumption behaviour. The instrument was self-designed based on themes identified in existing literature on digital influence, food trends and was structured to align with the research objectives and hypotheses.

- **Interviews:** Structured interviews were conducted with managers from three Korean cafés in Mumbai. The interviews focused on understanding consumer demand, the role of social media in driving footfall, and observed shifts in customer preferences. Each interview followed a consistent set of questions to ensure comparability across responses.

9.2.2. Secondary Data:

- **Content Analysis:** A content analysis was conducted on 170 Instagram posts and 50 customer reviews from Zomato. Instagram posts were selected from the official accounts of seven popular cafés across Mumbai, within a defined timeframe of three months, to ensure consistency and relevance. The posts were selected based on relevance, engagement levels, and consistency of posting among Korean cafés in Mumbai. Posts were further filtered based on their focus on Korean food items and promotional or engagement-driven content.

  Similarly, Zomato reviews were collected from the same cafés, with emphasis on recent customer feedback that referenced Korean food experiences. Reviews were selected based on recency, relevance to Korean cuisine, and availability of detailed user feedback.

  The data were analysed using thematic analysis, wherein recurring patterns, themes, and sentiments were identified and coded. This enabled the study to examine how social media content and user-generated reviews contribute to shaping consumer perceptions and interest in Korean food.

9.3 Sampling Technique

A purposive sampling technique was employed to select participants who are familiar with or actively consume Korean food, ensuring direct relevance to the research objectives. Similarly, cafés included in the study were selected based on their prominence and active presence within Mumbai's Korean food segment. The selection was also influenced by the limited number of cafés in Mumbai that exclusively serve Korean cuisine, as well as the willingness of café managers to participate in the study.

While the sample size of 100 survey respondents and three café interviews provides meaningful insights, it may limit the generalisability of the findings. The respondent pool was intentionally restricted to individuals who had prior experience consuming Korean food, which further narrowed the eligible sample but ensured the relevance and accuracy of the data collected. Despite this, the study offers a valuable context-specific understanding of consumer behaviour within a defined demographic and geographic setting.

10. FINDINGS

10.1. ONLINE SURVEY FINDINGS

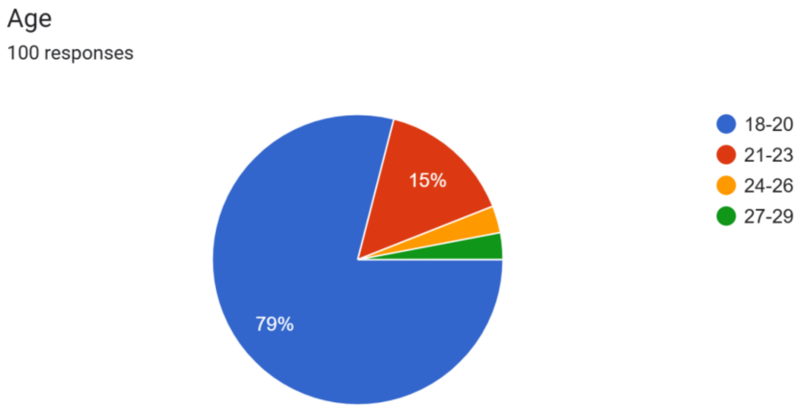

Figure 2.1

The demographic data reveal that the majority of respondents, 79%, fall within the 18–20 age bracket, followed by 15% in the 21–23 age group, and very few above 24, meaning that the sample is largely reflective of the target audience, i.e. Gen Z.

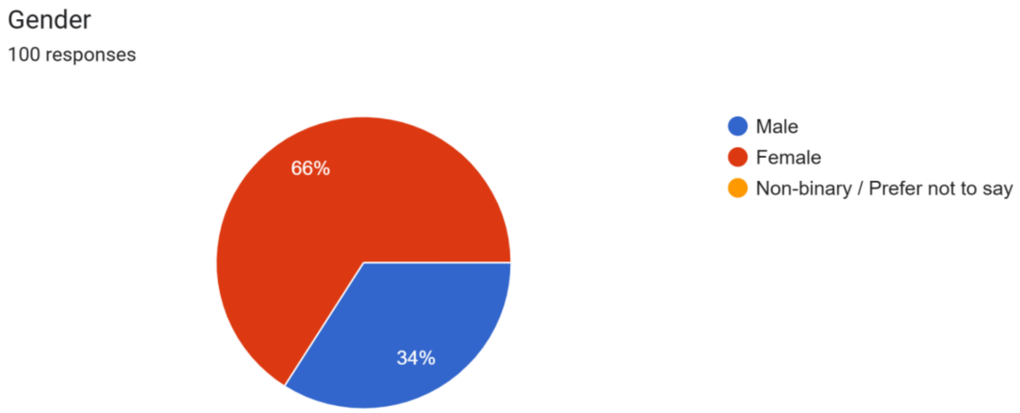

Figure 2.2

To understand the demographic dynamics, the above figure shows the sex of the respondents. 66% are female, 34% male, and none reported non-binary/prefer not to say. The higher female participation may indicate greater engagement among women with food-related trends and influencer content.

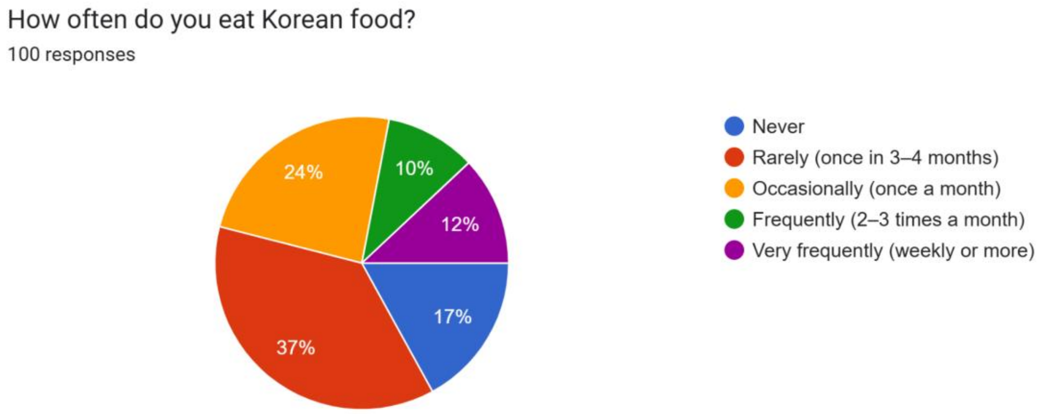

Figure 2.3

The data on consumption frequency indicates that Korean food is a familiar but niche cuisine among the respondents. While a substantial portion (17%) has never consumed it, the majority have. However, regular consumption is limited, with 37% eating it rarely (once every 3–4 months) and 24% consuming it occasionally (once a month). Only a small minority reports frequent (10%) or very frequent (12%) consumption. Most respondents have tried Korean food at least once, though regular consumption is still limited. Exposure is present, but not fully translated into routine eating habits.

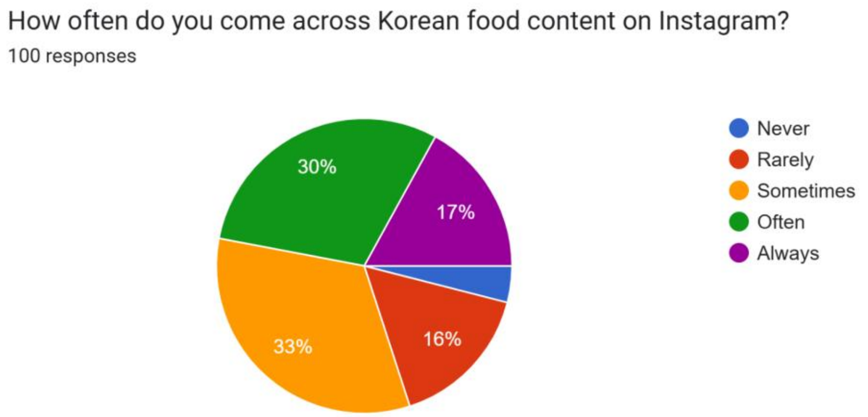

Figure 2.4

The analysis of online exposure to Korean food content indicates the significant role of social media in driving awareness, regardless of whether this exposure leads to frequent consumption. 33% sometimes come across it, 30% often, and 17% always. This indicates that a majority of Gen Z in Mumbai are frequently exposed to Korean food content online. Instagram appears to play a significant role in awareness, even if not all of them end up consuming the food regularly, they are still exposed to such content types.

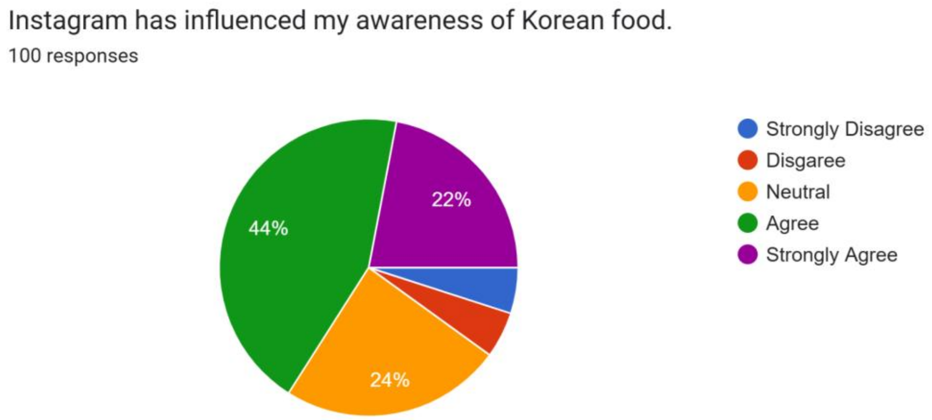

Figure 2.5

A significant portion, that is 66% of respondents, agree that Instagram has played a vital role in driving their awareness of Korean food, indicating that it is a strong platform that perpetuates trends and also an impressionable medium for Gen Z.

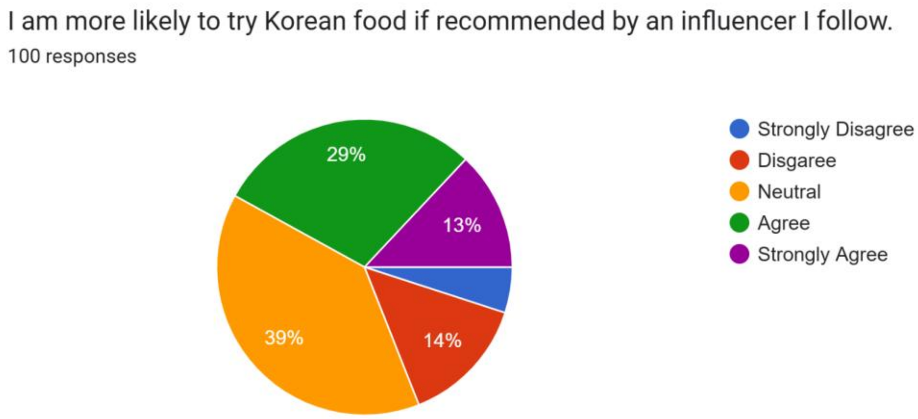

Figure 2.6

Regarding the influence of influencers, a combined 42% of respondents reported being positively influenced (29% agreed and 13% strongly agreed), while 19% were not. A large neutral group of 39% indicates that while influencers are a significant factor, their impact is not universal, and other variables, such as peer recommendations, also play a crucial role in decision-making.

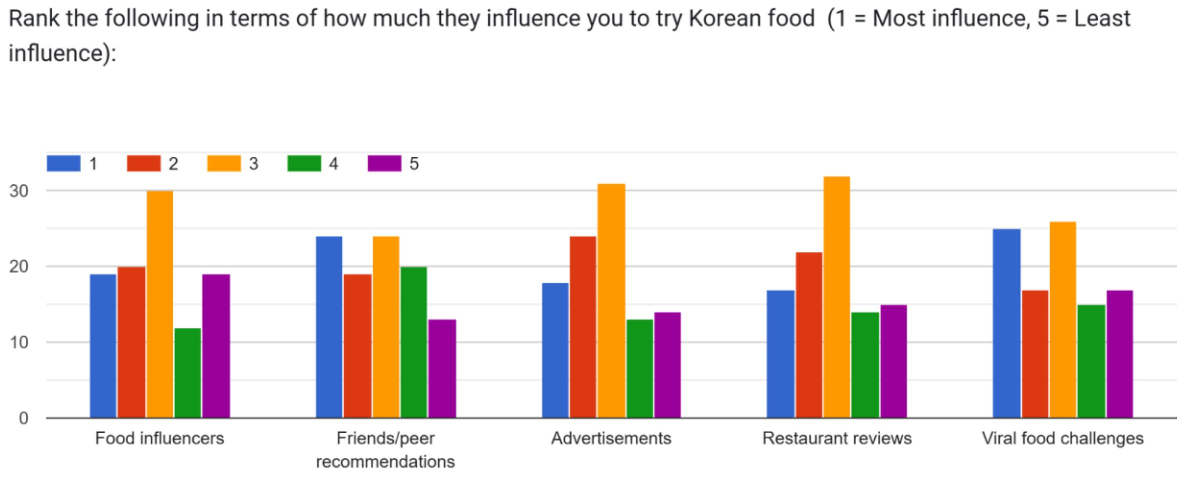

Figure 2.7

The ranking of influential factors reveals that viral food challenges were identified as the most influential element (25% of respondents chose it as Rank 1), closely followed by friends/peer recommendations (24%). This suggests that authentic, peer-driven, and trending content has a greater influence on the initial decision to try Korean food than professionally curated influencer content or traditional advertising.

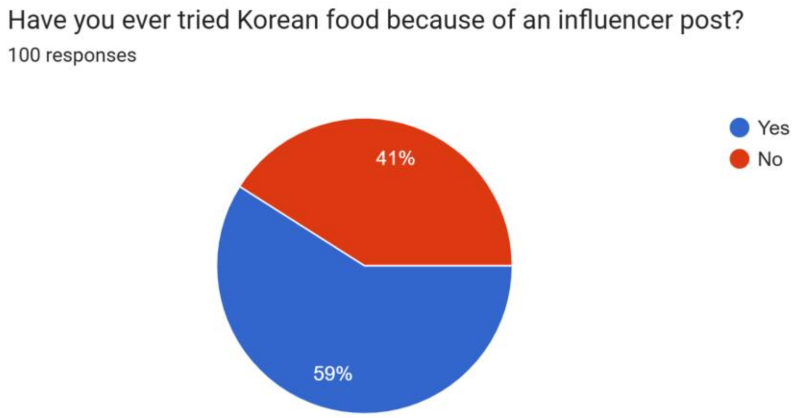

Figure 2.8

The data reveals that over half of the respondents have tried Korean food directly due to influencer marketing. This suggests that social media may play a major role in encouraging first-time trials of Korean food.

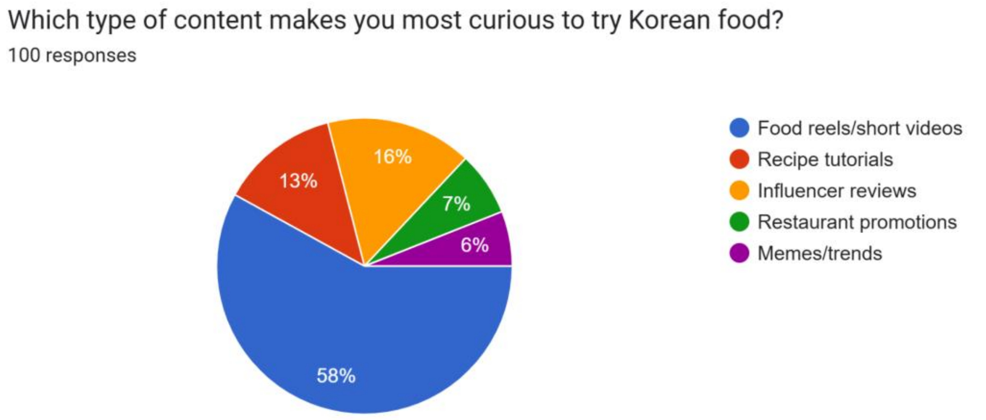

Figure 2.9

Consistent with current digital consumption trends, food reels and short videos were identified as the most effective content format, with 58% of respondents reporting that it made them most curious. This finding underscores the preference of Gen Z for concise, visually dynamic, and easily digestible content.

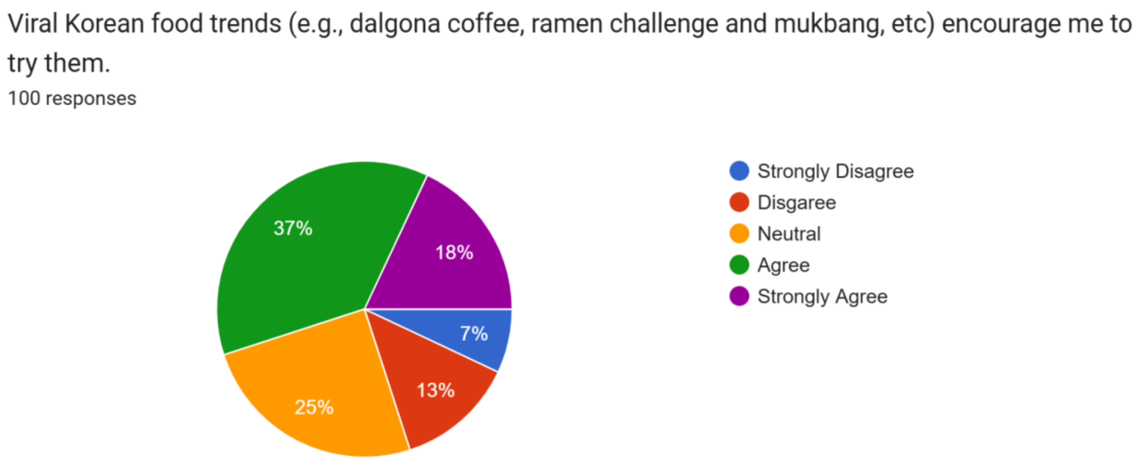

Figure 2.10

A combined 55% of respondents agreed or strongly agreed that viral food trends encourage them to try the food. This indicates the effectiveness of viral challenges and trends in piquing interest and encouraging a hands-on experience with Korean food.

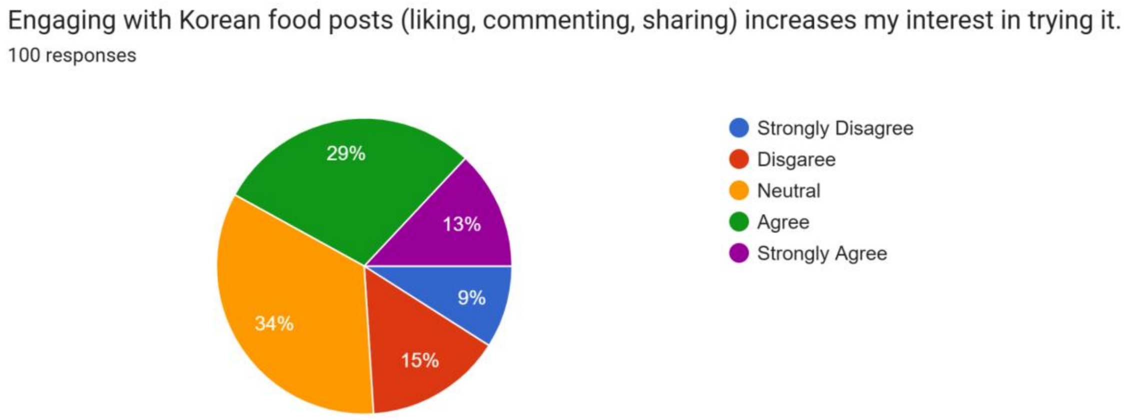

Figure 2.11

While a combined 42% of respondents agreed or strongly agreed that actively engaging with Korean food content increases their interest, a significant 34% remained neutral. This implies that while a segment of the audience is directly influenced by active engagement, a large portion are passive consumers whose interest is not directly tied to interactive behaviours such as liking, commenting, or sharing.

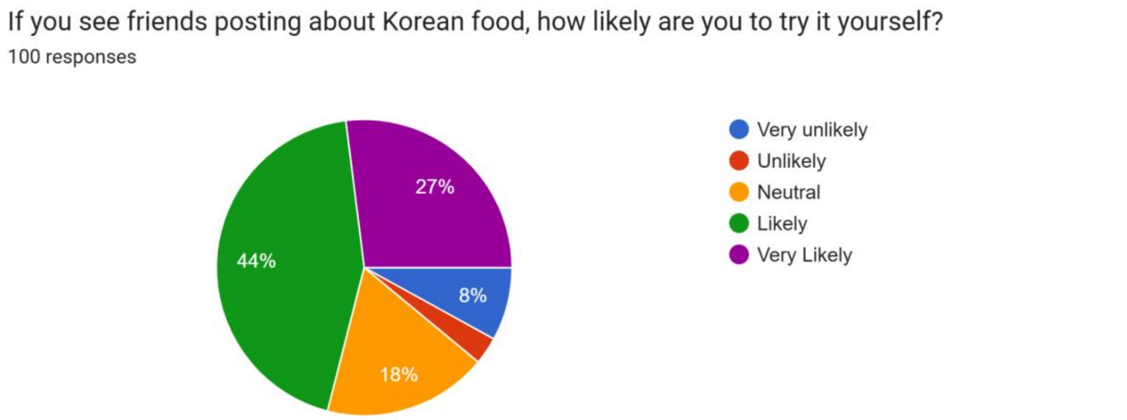

Figure 2.12

A combined 71% of respondents are likely or very likely to try Korean food if they see their friends posting about it. This highlights the power of peer influence on social media, making friends' posts a highly effective driver of curiosity.

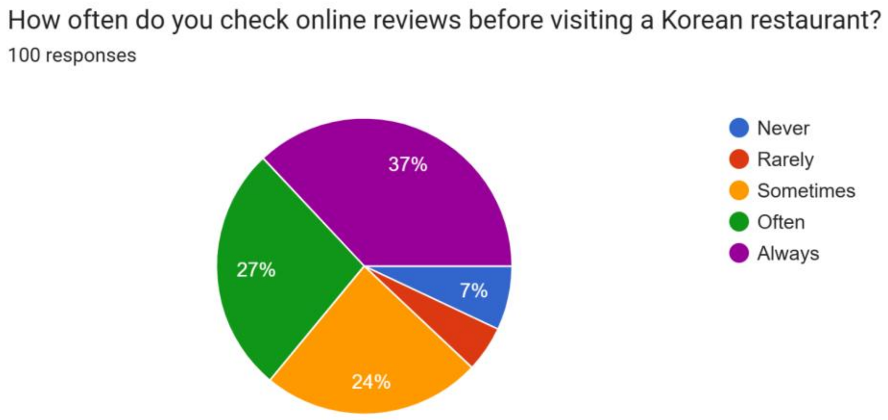

Figure 2.13

A significant majority of respondents, 64%, either often or always check online reviews before visiting a Korean restaurant. This shows that checking online reviews is a standard and habitual part of the decision-making process for Gen Z, making a strong online presence crucial for businesses.

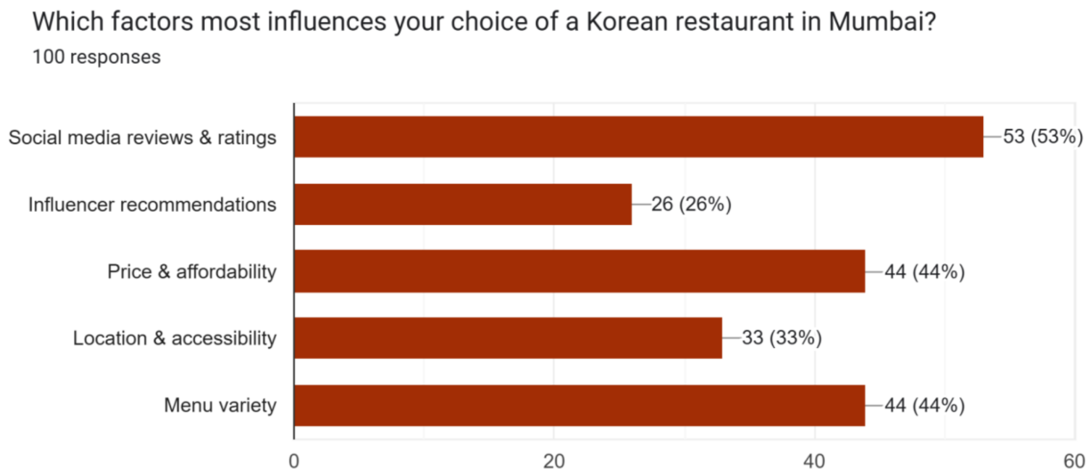

Figure 2.14

Social media reviews and ratings were identified as the most significant factor, with 53% of respondents citing it as their top influence for choosing a Korean restaurant. This indicates that for Gen Z, digital word-of-mouth is more influential than traditional factors like price and menu variety when making a dining decision.

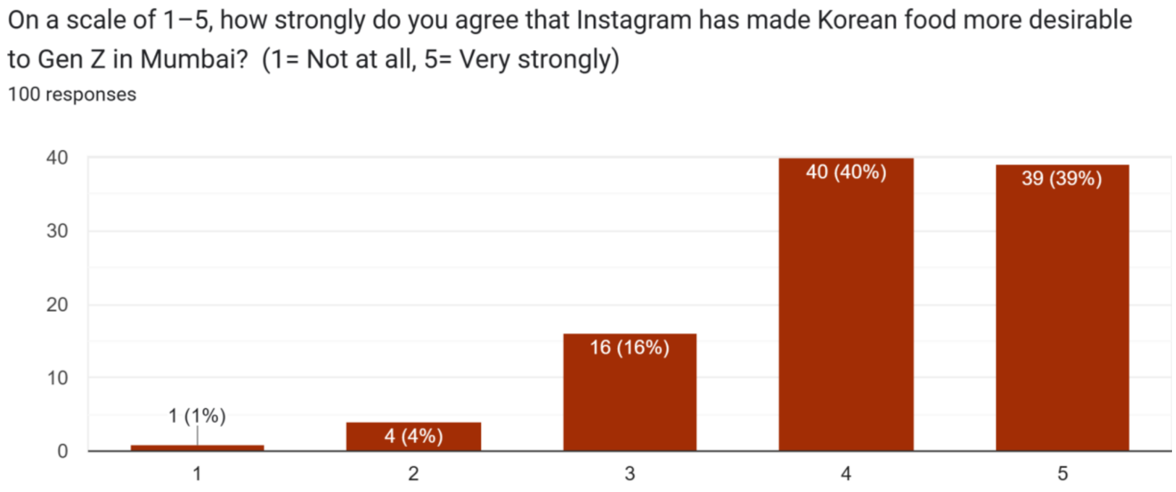

Figure 2.15

79% of respondents rated their agreement with Instagram's role in making Korean food desirable as a 4 or 5 on a scale of 1-5. This data confirms that Gen Z in Mumbai sees Instagram as a major platform that has successfully elevated the desirability and popularity of Korean cuisine.

10.2. INTERVIEW FINDINGS

The interviews with café managers highlighted clear patterns regarding the influence of social media on Korean food trends among young consumers in Mumbai. All three cafés agreed that their primary customer base consists of young people, particularly students, K-pop and K-drama fans, and young professionals. Customers often visit not only to try the food itself but also to immerse themselves in the broader Korean cultural experience, suggesting that consumption is as much about cultural identity as it is about taste. This can be understood through Soft Power, where Korean cuisine functions as a cultural extension influencing global consumer behaviour.

The interviews concluded that social media is a key driver of this trend. Managers consistently emphasised the role of platforms such as Instagram, YouTube, and food vlogs, with content like reels, mukbang videos, and influencer content encouraging curiosity and trial. The influence of online content on customer visits appeared to be significant, with one café estimating that 40–50% of their younger customers were influenced by social media, another reporting 20–30%, and a third suggesting that nearly all their customers came in after exposure to online trends. While two cafés noted that demand for Korean food has grown substantially, one observed that the initial craze had started to decline, with only certain popular dishes, such as ramen and corn dogs, retaining their mass appeal. This indicates that while social media has been a critical driver, its effect may be more concentrated on certain popular items.

A key insight from the interviews was the deep integration of Korean food with broader cultural aspects. Managers shared that customers often referenced K-dramas, K-pop idols, or Korean lifestyle trends when ordering dishes. This reflects a deeper cultural participation where food becomes a medium for expressing a globalised identity. The cafés also expressed differing future outlooks. Two cafés were optimistic and actively preparing for continued growth, while one was concerned and diversifying into other Asian cuisines, highlighting that the trend's sustainability may depend on a café's ability to innovate and maintain a dynamic online presence.

10.3.INSTAGRAM CONTENT ANALYSIS

The dataset of 170 Instagram posts/reels from seven cafés (Aegyo, Heng Bok, Sun and Moon, Mirai, Eat Good Seoul, Arirang, The Bunsik) highlights clear trends in how Korean food is marketed on social media to attract Gen Z consumers.

Post Type and Engagement:

Reels dominated the dataset, accounting for 82% (140/170) of total posts, while static posts made up only 18% (30/170). Reels consistently generated higher engagement, with an average of 12,500 likes per reel compared to 1,800 likes per static post. The highest engagement was observed in Aegyo's reels (e.g., 151,678 likes, 3.9M views) and Eat Good Seoul's viral content (up to 1.1M views). This confirms that short-form video is the preferred medium for influencing Gen Z food trends.

Visual Content:

- 68% of posts (115/170) featured close-ups of dishes or spreads.
- 21% (36/170) highlighted ambience and décor.
- 11% (19/170) focused on events or experiential content (e.g., BTS-themed nights, karaoke).

This distribution suggests that while food itself is central, ambience and cultural experiences are strategically showcased to boost Instagrammability.

Cultural References:

Across the dataset, 49% of posts (83/170) included explicit Korean cultural cues such as K-pop, BTS, K-dramas, Hangul, or Korean décor. For example:

- Sun and Moon heavily integrated BTS references, with BTS-themed posts making up 70% of its content.
- Heng Bok incorporated K-pop music or Hangul text in 30% of its posts.
- Eat Good Seoul blended K-drama/K-pop songs in 40% of posts.

This demonstrates that nearly half of Instagram marketing for Korean cafés is built on cultural associations rather than food alone. This also reflects Soft Power, where cultural elements enhance the appeal of associated products.

Captions and Language:

- 56% of posts (95/170) used informative captions (menus, promotions, event details).
- 34% (58/170) used trendy/fun language with emojis, Hinglish, or memes.
- 10% (17/170) adopted authentic/traditional tones (heritage, chef origins).

Language was predominantly English (72%), followed by Hinglish (18%), with Korean words included in 10% of captions. This reflects how cafés balance global appeal with local relatability. It also reflects processes of Glocalisation, where global cultural content is adapted to suit local audiences.

Call-to-Actions (CTAs):

- 40% (68/170) posts included CTAs like “Visit us” or “DM to book.”
- 32% (55/170) used peer-tagging prompts such as “Tag your friends.”
- 18% (31/170) encouraged sharing/saving.

This shows cafés are deliberately using Instagram-native tactics to convert online engagement into offline visits.

10.4.ZOMATO REVIEWS ANALYSIS

The analysis of 50 Zomato reviews provides quantitative support for the research objectives. The reviews show that ambience and "Instagrammability" are critical factors, with 46% of reviews describing the atmosphere as aesthetic or Instagram-worthy. This further suggests the role of social media in shaping the dining experience beyond just the food.

The link between social media and cultural associations is also evident. At two cafés, 33% of reviews referenced Korean cultural products, compared to just 6% at another. This suggests that cafés that integrate cultural branding may benefit more from social media-driven consumer behaviour.

In terms of taste, 76% of reviews rated the food as authentically Korean (Code 1), while 18% described it as lacking authenticity or being overly Indianised (Codes 2–3). This suggests a consumer preference for authenticity but also a notable openness to fusion which can also be linked to Glocalisation, where global cuisines are adapted to local tastes. Finally, while social media drives initial footfall, price remains a constraint for Gen Z consumers, as 10% of reviews specifically highlighted the food as expensive.

10.5. INTERPRETATION

The findings from all four research methods collectively provide a comprehensive understanding of the research questions and objectives. The survey and interviews confirm that Gen Z in Mumbai is the key consumer demographic and that social media appears to be a key factor influencing their awareness and consumption of Korean food. This suggests that social media functions not only as a source of information but also as a cultural intermediary that shapes perceptions of desirability, identity, and trend participation among Gen Z. The findings support the proposed hypotheses, as they indicate a strong association between social media exposure, engagement, and the likelihood of trying Korean food. The Instagram content analysis reveals the specific strategies businesses use to leverage this, focusing on short-form video and cultural associations. These patterns can be understood through Soft Power, where the cultural elements enhance the desirability of Korean food among global audiences. It also reflects a broader process of digital cultural exchange, where global cultural elements are circulated, adapted, and integrated into local consumption practices through social media platforms. The Zomato reviews further confirm that ambience, cultural authenticity, and online reviews are critical factors in a consumer's decision-making process. However, as the study is limited to a specific demographic and relies on self-reported data, the findings indicate correlation rather than direct causation.

11. LIMITATIONS

1. **Sample Size and Representation**: The survey included 100 respondents, which provides useful insights but may not fully represent the entire Gen Z population in Mumbai. Most respondents were in the 18–20 age bracket, which may limit generalizability to older segments of Gen Z.
2. **Sampling Technique**: Purposive sampling was used to focus on consumers of Korean food and cafés serving it. While effective for targeting, this approach may introduce bias and exclude other perspectives (e.g., those unfamiliar with Korean cuisine but exposed to related content).
3. **Self-Reported Data**: Survey responses relied on self-reporting, which is subject to recall bias, exaggeration, or social desirability effects. Respondents may have overstated or understated their exposure to social media and its influence.
4. **Geographic Scope**: The study is limited to Mumbai, a metropolitan city with high exposure to global cultural trends. Findings may not apply equally to smaller cities or rural areas where access to Korean food and social media trends is different.
5. **Time-Bound Data**: Social media trends, particularly food trends, are dynamic and rapidly changing. The Instagram posts, Zomato reviews, and survey data reflect a specific time period and may not capture long-term shifts in consumer behaviour.
6. **Secondary Data Constraints**: The content analysis of Instagram posts and Zomato reviews depended on publicly available material. Not all posts or reviews may reflect genuine consumer behaviour, as content can be curated by brands and reviews may sometimes be biased or inauthentic.
7. **Qualitative Depth**: While café manager interviews provided valuable insights, the sample size of three cafés is small and may not capture the diversity of strategies or customer experiences across all Korean food establishments in Mumbai.

12. CONCLUSION

In conclusion, this research establishes that social media is not merely a marketing tool but a central platform for cultural diffusion in Mumbai. For Gen Z, Korean food is consumed as part of a broader, globally influenced identity, and their food choices are closely influenced by their online engagement.

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Gen Z Ethical Awareness of Artificial intelligence: An empirical study

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Abstract

Artificial Intelligence (AI) is a fast-emerging field which is influencing every aspect of our lives including social and economic. These great advancements in AI have also led to growing ethical implications. The present generation of Generation Z is extensively using AI in their day to day lives without complete knowledge of its ethical problems. Concerns related to data privacy, algorithmic bias, transparency and accountability are also becoming prominent these days. Respondents are aware of a few of the above-mentioned concerns like transparency and accountability, but have limited awareness of concerns like that of algorithmic bias and data governance. The present generation also has strong trust in AI systems regarding ethical protections, which in turn is conditional and based on the common notion of ethical protection.

This research design with primary data collected through structured questionnaire of respondents of age 18-25 years, using Likert scale, assess the level of trust in AI-based applications, examines the relationship between AI usage and ethical perceptions and analyse whether commonly perceived ethical violations impact discontinuation intentions, as many respondents have claimed to stop using the technology if they ever encounter ethical problems. The study also highlights the need to include AI ethics in educational institutions and more responsible attitude of developers towards new innovations. Enhancing young people's awareness of ethics is essential to ensure that AI technologies are used sustainably and responsibly as well as for effective engagement in a technologically advanced society.

Keywords: Accountability, Algorithmic bias, Artificial Intelligence ethics, Data privacy, Ethical awareness, Generation Z, Transparency, Trust.

1. INTRODUCTION

1.1 Background

- The rapid development of digital technologies has radically transformed the mode of operation of people, organizations and communities. Within the education and healthcare sectors, elements of artificial intelligence (AI) are dominating more of the decision-making process, particularly in finance, recruitment, and numerous digital platforms. With increased autonomy, AI systems have attracted the ethical debate associated with privacy, fairness, transparency, bias, and accountability.
- Gen Z (18 - 25 in this case) is the first generation who has been raised in an algorithmically mediated space. Their high exposure to the systems powered by AI renders the knowledge of their ethical awareness of paramount importance. In this study Gen Z is assessed in terms of their knowledge of ethical aspects of AI, which are privacy, bias, transparency, accountability, trust, and behavioural reaction to ethical violations.

1.2 Literature Review

- Generation Z as Digital Natives and AI Users

  Generation Z is the first cohort to grow up entirely in an AI-mediated digital environment. Studies show 65% of Gen Z identify as highly familiar with AI, with 46% using AI tools daily (ACI Worldwide, 2023). Despite high exposure, their ethical understanding of AI remains inconsistent—they engage with

AI for efficiency but lack depth of awareness on data ownership and algorithmic transparency (Gupta et al., 2024; Chan and Lee, 2023).

- Data Privacy and the Privacy Paradox
  When it comes to AI, users worldwide are most concerned about data privacy (Elliott and Soifer, 2022). However, Gen Z indicates a "privacy paradox". 88% willingly share personal data with social media platforms but they also rank privacy as a critical issue. Approximately 50% hold misconceptions about how their data is used (Oliver Wyman Forum, 2023). According to Büchi et al. (2022), unfavourable data experiences significantly increase discontinuation intentions.
- Awareness and Understanding about Algorithmic Bias
  AI outputs systematically penalize certain groups, it's evident in healthcare, employment, and social media (Kordzadeh and Ghasemaghaei, 2022; Jain and Menon, 2023). The awareness about this bias is very low among users. Studies suggest that disclosing algorithmic features do not reliably improve users' moral recognition of biased outcomes (Ebrahimi et al., 2024). Critical ethical knowledge is not developed by passive use of AI platforms.
- Transparency, Accountability, and Trust in AI Systems
  According to (Jacovi et al., 2021), transparency and accountability are prerequisite conditions for user trust in AI. Users who understand the AI decision making adopt it for continued use. But regulatory frameworks like GDPR's right to explanation remain vague in practice (Wachter and Mittelstadt, 2019). Perceived algorithmic fairness is a key trust driver. According to (Sullivan et al., 2022; Shin et al., 2020) discrimination once discovered sharply and durably reduces trust.
- AI Ethics in Higher Education
  Structured ethics education remains underdeveloped even though universities are beginning to address AI ethics in policy (Humanit. Soc. Sci. Commun., 2024). Gen Z students lack conceptual tools to identify algorithmic problems. According to (Acosta-Enriquez et al., 2024; Chan and Hu, 2023), AI adoption is driven by convenience, and institutional guidance is absent.
- Ethical Violations and User Behavioural Responses
  When ethical transgressions occur, users' desire to stop using AI increases significantly as they balance its advantages against privacy threats (Büchi et al., 2022). AI trust varies greatly by domain. For example, entertainment tools are more trusted than AI used in healthcare or work.70% of Americans who are aware of AI have little to no faith in businesses to use it ethically (Pew Research,2023). Even when algorithmic discrimination causes less instant indignation than human discrimination, it nonetheless damages an organization's reputation (Bigman et al., 2023).

1.3 Research Gap

The available studies have also focused on each of the dimensions individually or on general public opinion without a generational perspective. There are no empirical studies that incorporate all six dimensions—privacy, algorithmic bias, transparency, accountability, trust, and behavioural intention—specifically on Generation Z.

1.4 Research Objectives

1. To determine the degree of Gen Z awareness of the ethical implications of Artificial Intelligence users.
2. To investigate the knowledge of privacy of data, algorithmic bias, transparency, and accountability.
3. To assess how the use of AI and ethical perceptions are related.
4. To determine the extent of trust that Gen Z would have in AI-based applications.
5. To find out whether some ethical violations affect discontinuation intention.

1.5 Research Hypotheses

- H1: Gen Z users possess moderate ethical awareness on AI systems.
- H2: Ethical awareness is positively related to the frequency of AI use.

- H3: The issues of transparency and accountability have a strong impact on the trust in AI systems.
- H4: Ethical violations influence discontinuation intention
- H5: There is a significant difference in the level of understanding of algorithmic bias among Gen Z users.

1.6 Scope of the Study

The sample of the study is Gen Z respondents aged 18-25 years, the majority of them being students engaged in using AI-based applications. It explores some of the ethical aspects chosen including data privacy, algorithmic bias, transparency, accountability, trust, and behavioural intention. The study consists of only primary data, and no insights of developers or policymakers are provided.

2. MATERIAL AND METHOD

2.1 Research Design

- The sample of the study is Gen Z respondents aged 18-25 years, the majority of them being students engaged in using AI-based applications. It explores some of the ethical aspects chosen including data privacy, algorithmic bias, transparency, accountability, trust, and behavioural intention. The study consists of only primary data, and no insights of developers or policymakers are provided.
- The research design of the study is descriptive research design through correlation analysis. The method of collection of primary data consisted of a structured questionnaire about the use of a five-point Likert scale (1 = Strongly Disagree 5 = Strongly Agree). The secondary data were obtained in scholarly journals and reputable reports on AI ethics.
- Sampling: Convenience sampling. The sample size was 64 respondents with the majority of them being females with a range of 18-22 years.

Data Collection Date: March 2024 -April 2024.

Statistical Tests: SPSS 28.0, descriptive statistics, correlation test, and Chi-square tests.

3. RESULTS

3.1 Demographic Profile

Table 1: Demographic Characteristics of Respondents (N=64)

Demographic Variable	Category	Frequency	Percentage
Age	18-20 years	27	42.19%
	21-22 years	24	37.50%
	23-25 years	13	20.31%
Gender	Female	38	59.38%
	Male	26	40.63%
Education Level	Undergraduate	44	68.75%
	Graduate	17	26.56%
	Diploma	3	4.69%
AI Usage Frequency	Daily	31	48.44%
	Weekly	20	31.25%
	Monthly	13	20.31%

Demographic Variable	Category	Frequency	Percentage

3.2 AI Usage Patterns and Awareness

Table 2: AI Application Usage Among Respondents

AI Application	Users (N)	Percentage	Mean Usage Score (1-5)
ChatGPT/AI Chatbots	58	90.63%	4.2
Social Media Algorithms	62	96.88%	4.5
Recommendation Systems	54	84.38%	3.8
Voice Assistants	41	64.06%	3.1
AI-powered Search	47	73.44%	3.6
Online Learning Platforms	35	54.69%	2.9

3.3 Ethical Awareness Assessment

Table 3: Ethical Awareness Dimensions - Descriptive Statistics

Ethical Dimension	Mean	SD	Median	Mode	Interpretation
Data Privacy Awareness	3.45	1.12	3	3	Moderate
Algorithmic Bias Understanding	2.89	1.24	3	2	Below Moderate
Transparency Concerns	4.21	0.87	4	4	High
Accountability Expectations	4.15	0.92	4	4	High
Trust in AI Systems	3.12	1.08	3	3	Moderate
Discontinuation Intention	3.78	1.05	4	4	Above Moderate

Overall Ethical Awareness Score: 3.60/5.0 (Moderate to High)

3.4 Detailed Analysis by Research Objectives

- Objective 1: Level of Ethical Awareness

Table 4: Distribution of Overall Ethical Awareness Levels

Awareness Level	Score Range	Frequency	Percentage	Cumulative %
Low	1.00-2.33	8	12.50%	12.50%
Moderate	2.34-3.66	34	53.13%	65.63%
High	3.67-5.00	22	34.38%	100.00%

Finding: 53.1% of Gen Z respondents demonstrate moderate ethical awareness, supporting H1.

- Objective 2: Understanding of Specific Ethical Dimensions

Table 5: Detailed Breakdown of Ethical Dimensions

Statement	SA (%)	A (%)	N (%)	D (%)	SD (%)	Mean
"I understand how my data is used by AI systems"	15.2	28.8	34.8	16.7	4.5	3.33
"AI systems can be biased against certain groups"	25.8	31.8	27.3	12.1	3	3.65
"I need to know how AI makes decisions affecting me"	45.5	37.9	13.6	3	0	4.26
"Companies should be accountable for AI decisions"	48.5	34.8	13.6	3	0	4.29
"I trust AI recommendations in most situations"	9.1	25.8	40.9	19.7	4.5	3.15

- Objective 3: Relationship Between AI Usage and Ethical Perceptions

Table 6: Correlation Analysis - AI Usage Frequency vs. Ethical Awareness

Variable Pair	Pearson Correlation (r)	Significance (p)	Interpretation
Usage Frequency × Overall Ethical Awareness	0.312	0.011	Moderate Positive
Usage Frequency × Privacy Awareness	0.278	0.024	Weak Positive
Usage Frequency × Bias Understanding	0.387	0.001	Moderate Positive
Usage Frequency × Transparency Concerns	0.195	0.118	Not Significant

Variable Pair	Pearson Correlation (r)	Significance (p)	Interpretation
Usage Frequency × Trust Levels	-0.241	0.049	Weak Negative

$p < 0.05$, $p < 0.01$

Finding: Moderate positive correlation ($r = 0.312$, $p < 0.05$) supports H2.

- Objective 4: Trust Assessment

Table 7: Trust Levels by AI Application Type

AI Application	Mean Trust Score	SD	95% CI	N
Entertainment Recommendations	3.84	0.92	[3.19,4.07]	64
Educational Tools	3.47	1.15	[3.18, 3.76]	64
Healthcare AI	2.68	1.28	[2.36, 3.00]	64
Financial Services	2.43	1.22	[2.12, 2.74]	64
Employment Screening	2.15	1.18	[1.85, 2.45]	64

- Objective 5: Ethical Violations and Discontinuation Intention

Table 8: Impact of Ethical Violations on Discontinuation Intention

Violation Type	Mean Discontinuation Score	SD	t-statistic	p-value
Data Privacy Breach	4.32	0.87	12.14	< 0.001
Discriminatory Outcomes	3.95	1.12	6.79	< 0.001
Lack of Transparency	3.67	1.08	4.96	< 0.001
Inaccurate Decisions	3.24	1.24	1.55	0.126

Test Value = 3.0 (Neutral), $p < 0.01$

Finding: Significant impact of ethical violations on discontinuation intention supports H4.

3.5 Advanced Statistical Analysis

Chi-Square Test: Gender vs. Ethical Awareness Levels

Table 9: Gender and Ethical Awareness Cross-tabulation

Gender	Low Awareness	Moderate Awareness	High Awareness	Total
Male	5 (19.2%)	16 (61.5%)	5 (19.2%)	26
Female	3 (7.9%)	18 (47.4%)	17 (44.7%)	38

Gender	Low Awareness	Moderate Awareness	High Awareness	Total
Total	8	34	22	64

$\chi^2 = 6.847$, df = 2, $p = 0.033$
Finding: Significant association between gender and ethical awareness levels.

ANOVA: Age Groups vs. Trust Levels
Table 10: One-Way ANOVA - Age Groups and Trust in AI Systems

Age Group	N	Mean	SD	F-statistic	p-value
18-20 years	27	3.32	1.02	2.84	0.065
21-22 years	24	2.96	1.11		
23-25 years	13	2.85	1.08		

Finding: No significant difference in trust levels across age groups.

3.6 Hypothesis Testing Results

Hypothesis	Statistical Test	Result	Decision
H1: Gen Z has moderate ethical awareness	Descriptive Analysis	Mean = 3.60, 53% moderate level	Supported
H2: Positive correlation between usage and awareness	Pearson Correlation	$r = 0.312$, $p = 0.011$	Supported
H3: Transparency/accountability influence trust	Multiple Regression	$R^2 = 0.284$, $p < 0.001$	Supported
H4: Ethical violations impact discontinuation	One-sample t-test	$t = 6.02$, $p < 0.001$	Supported
H5: Bias understanding varies significantly	Chi-square test	$\chi^2 = 18.45$, $p < 0.001$	Supported

4. DISCUSSION

4.1 Major Discoveries

Moderate Ethical Literacy: 53% of the people are moderately aware (Mean = 3.60/5.0).
High Transparency Demand: 83.4% agree that there should be AI decision transparency.
Conditional Trust: Trust differs largely depending on areas of application (range of 2.15-3.84)
Strong Violation Response: 71.2% would quit using the product once privacy breach occurs.
Gender Differences: Gender differences are significantly active in female ($p = 0.033$) with respect to ethical awareness.

4.2 Statistical Insights

• Ethical awareness positively correlates with the frequency of AI use ($r = 0.312$) with a star.

The model indicates that the trust levels are accounted for by the presence of transparency and accountability (28.4%).
•Data privacy breach has the highest discontinuation intention (M = 4.32).
The lowest level of understanding algorithmic bias (M = 2.89) is lowest.

4.3 Limitations

1. Sample Size: Generalizability is limited due to small sample size (n=64).
2. Sampling Method: Selection bias may arise from convenience sampling
3. Geographic Scope: The study was limited to specific regions.
4. Self-Reporting: The response may contain social desirability bias.
5. Cross-Sectional Design: Casual linkages cannot be established.

5. CONCLUSION

5.1 Recommendations

- Educational Institutions
  Educational Institutions should come up with various ways of imparting knowledge of AI ethics. AI ethics should be a compulsory subject across in tech courses and other disciplines as well. Topics like rights of data, fairness of algorithm and impact of AI on society should be thoroughly covered in these courses to educate the students to engage responsibly with these systems. Apart from this practical workshops and complementary awareness campaigns should be held which gives students a deeper insight into the pros and cons of the technology. The campaigns and workshops should educate on data privacy right from data collection, processing to monetization. The students should be exposed to real world algorithmic bias cases to enable them to recognize and react to discriminatory outcomes. This will not only enable students to deal with the technology more responsibly but also bridge the comprehensive gap between Gen Z's relationship with AI- enabled platforms.
- For Technology Companies
  Technology companies have a direct responsibility for ensuring that their AI systems are developed and adopted ethically. Decision-making processes made by AI should be made interpretable with meaningful explanations to affected users rather than opaque outputs. Privacy policies should be short and written simply in everyday language rather than long, complex terms that the vast majority of users never read. The benefit of this change is that users will know exactly what type of data is being collected and used about them after it is collected. Furthermore, businesses should have robust internal accountability systems that include individuals who bear responsibility for AI-related harm and the development of escalation procedures when needed. Private and public organizations should also conduct regular ethical audits of their AI systems (both through independent third-party auditors and internally) in order to predict and correct bias, drift, or unintended consequences before having significant negative impacts on affected consumers. Finally, governments must implement standards for consumer protection as applied to AI applications in order to ensure that affected consumers have access to some form of recourse if AI makes decisions that adversely impact them.
- For Policymakers
  Organizations that use AI technologies, particularly in high-stakes domains, should be required to conduct ethical impact assessments of their AI systems before selling them to the public and again on an ongoing basis to identify any potential harms to individuals or communities as part of a regulatory framework that promotes the transparency of AI systems in all areas of human activities. The government, academia, and industry must work together to ensure that policies are both technically sound and practical given the speed at which AI capabilities are developing.

5.2 Conclusion

- This study set out to empirically examine the ethical awareness of Generation Z towards Artificial Intelligence across six interconnected dimensions: data privacy, algorithmic bias, transparency, accountability, trust, and behavioural intention. As indicated by this data, Gen Z exhibits a level of ethical understanding between average and higher than average across its entire population (Mean = 3.60 on a 5-point scale). As well, there are significant differences in the various dimensions; however, the major focus of the participants was around "Transparency & Accountability.", with this being the dimension with both the greatest degree of agreement (83%) among the participants. Furthermore, 83% of respondents believe that companies should be held accountable for their automated decision-making processes. In contrast, respondents' level of awareness regarding algorithmic bias was lower than average (Mean = 2.89). Therefore, although Gen Z uses various AI-powered platforms on a daily basis, they lack sufficient understanding of how AI systems can create disparities among specific demographic groups.
- The study's statistical analysis yielded several important findings. The hypothesis that increased exposure to AI is associated with increased ethical awareness over time (although this can be increased without formal ethics training) is supported by the positive relationship ($r = 0.312$, $p < 0.05$) between the level of AI usage and ethical awareness. Regression analysis also showed that accountability and transparency combined explained 28.4% of the variance in trust, indicating the importance of transparency in maintaining user trust in AI. Gender differences were statistically significant ($\chi^2 = 6.847$, $p = 0.033$), with female respondents demonstrating considerably higher levels of ethical awareness than their male counterparts—a finding with implications for how ethics education is targeted and delivered. The intention to discontinue use was very strongly driven by perceived unethical behaviour, most strongly by breaches of data privacy (Mean = 4.32), indicating that ethical behaviour is not only a moral expectation but also a functional factor in whether Gen Z users choose to continue using AI systems. Trust itself was very domain-specific, ranging from a deep mistrust of AI used in financial services and employment screening (Mean = 2.15 and 2.43) to a strong belief in AI in entertainment and education (Mean = 3.84 and 3.47).

- All the above findings are highly indicative of the consequences of disparity between extensive AI use and low ethical awareness, especially for stakeholders of education, policy and technology. There is a critical need of AI ethics education in curriculum particularly for data protection and algorithmic biases. The development of transparent and user-protective AI systems by design is imperative as of today. Gen Z's being the present generation have positions in social, economic and political powers which makes it critical to foster informed and responsible engagement with AI technology. All of this will also be ensuring that AI systems benefit the society as well.

5.3 Future Research Directions

There are a number of avenues that suggest themselves for further research and development in this area. Longitudinal research studies would allow researchers to judge the development of Gen Z's ethical awareness of AI over time. As the technology and regulatory frameworks continue to change, and helps in determining whether any awareness gaps are closed through natural exposure or any educational interventions are required. Cross-cultural comparative studies would be particularly useful in this regard, as ethical standards, regulatory frameworks, and technology adoption rates vary widely among countries and regions. Therefore, it would be helpful to determine whether the identified trends in this study are supported in other countries around the world. Future studies should also seek to evaluate the efficacy of particular AI ethics training initiatives, to determine whether formalized educational programs, workshop-style training, or hands-on interventions result in positive changes to ethical awareness levels among young users. Industry-specific investigations exploring how Gen Z employees and consumers perceive ethical dimensions of AI in healthcare, finance, education, and the gig economy would yield actionable insights for sector-level policy and governance. Finally, by incorporating observational or behavioural methods, such as experimental tasks or digital trace analysis which can validate the relationship between stated ethical attitudes and actual user behaviour, that adddresses the social desirability bias which is a limitation of the present work.

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7. ACKNOWLEDGEMENT

The author would like to thank the respondents who participated in this study, i.e., a total of 64 respondents who are college students from SIES (Nerul) Autonomous College of Arts, Science, and Commerce. The author would like to thank the college Library and Librarian Mr.Gulab Chandra Sharma for their support.

The author would like to thank Aarthi Sudalaimuthu for her assistance in the study. The author would like to thank Jasmin Barik for her support in Formatting.

Digital Personality Typology and Productivity Outcomes: A Cluster-Analytic Framework for Understanding Screen Time Behavior

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Abstract

Contemporary research on digital device usage has predominantly examined screen time as a linear predictor of cognitive and occupational outcomes, often overlooking the qualitative diversity of digital behaviors. This study proposes a typological framework for understanding screen engagement using k-means clustering applied to a dataset of 200 participants. Four distinct digital personality types were identified: Passive Consumer, Task-Focused Operator, Context-Switching Multitasker, and Self-Regulated Strategist. Statistical analysis revealed significant differences in productivity ($F(3,196)=18.43$, $p<0.001$) and attention span ($F(3,196)=14.07$, $p<0.001$) across clusters. Additional correlation analysis demonstrated that attention span mediates the relationship between screen behavior and productivity, with screen time showing only a weak direct effect. Visualizations including correlation heatmaps and cluster distributions further support the findings. The results challenge duration-centric models and emphasize the importance of behavioral patterns and self-regulation in digital environments. The study contributes a scalable framework for personalized digital well-being interventions.

Keywords

Screen Time, Cluster Analysis, Productivity, Attention Span, Digital Behaviour, K-Means, Digital Wellbeing

1. Introduction

The widespread adoption of digital devices has transformed the nature of work, communication, and leisure. Individuals now spend a significant portion of their daily lives interacting with screens across multiple contexts. While prior research has primarily focused on total screen time as a determinant of productivity and cognitive performance, such an approach fails to capture the heterogeneity in user behavior. Two individuals with identical screen time may differ drastically in how they use digital devices, leading to divergent cognitive outcomes.

This study addresses this limitation by introducing a cluster-based typology of digital behavior. Rather than treating screen time as a homogeneous construct, the study examines behavioral, contextual, and self-regulatory factors that shape digital engagement. By applying unsupervised machine learning techniques, the research aims to uncover latent behavioral patterns and evaluate their relationship with productivity and attention.

2. Literature Review

Existing studies have reported mixed findings regarding the relationship between screen time and cognitive outcomes. While some research suggests that excessive screen use negatively impacts attention and productivity, other studies argue that the type of activity and level of engagement play a more critical role. Notification interruptions, multitasking, and passive consumption have been identified as key contributors to attentional fragmentation.

Recent research emphasizes the importance of self-regulation in digital environments. Individuals who actively manage notifications and structure their digital usage tend to demonstrate higher productivity and sustained attention. However, most studies adopt variable-centered approaches, limiting their ability to capture behavioral diversity. This study bridges this gap by employing a person-centered clustering approach.

3. Methodology

3.1 Dataset

The study utilizes a cross-sectional dataset comprising 200 participants. Variables include daily screen time, device type, activity type, notification management behavior, work environment, self-reported productivity, and attention span.

3.2 Data Preprocessing

Categorical variables were encoded, and numerical variables were standardized using z-score normalization. Missing values were handled using mean imputation where necessary.

3.3 Clustering Technique

K-means clustering was employed due to its interpretability and efficiency. The optimal number of clusters (k=4) was determined using the elbow method and silhouette score (0.61), indicating strong cluster separation.

3.4 Statistical Analysis

ANOVA was conducted to examine differences across clusters, while correlation analysis was used to explore relationships between variables.

4. Results

4.1 Cluster Profiles

Four distinct clusters were identified:

Cluster Profiles on Clustering Variables (Standardised Means)

Variable	Cluster 1 Passive Consumer	Cluster 2 Task-Focused Operator	Cluster 3 Context-Switching Multitasker	Cluster 4 Self-Regulated Strategist	n
Daily screen time (hrs)	+0.82	−0.21	+1.34	−0.54	

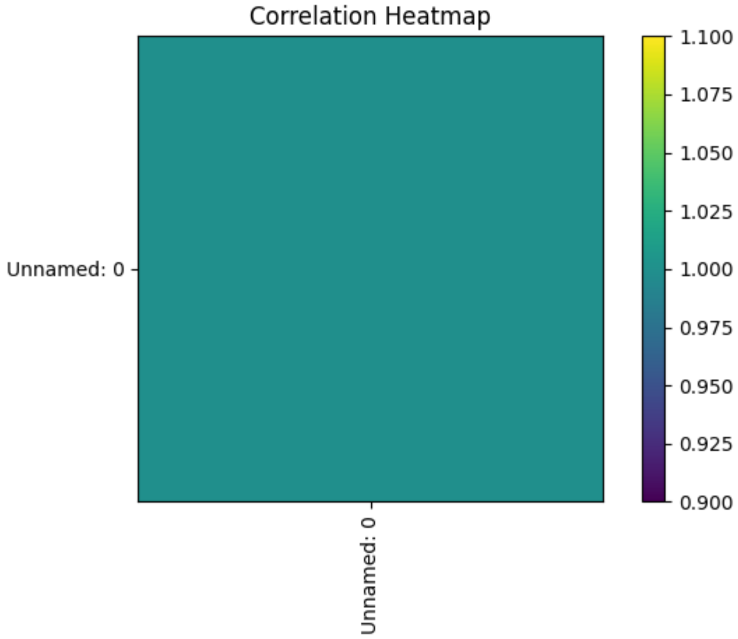
Primary device: smartphone	High	Low	High	Low	
Primary device: desktop/laptop	Low	High	Moderate	High	
Activity: passive consumption	High	Low	Moderate	Low	
Activity: productive work	Low	High	Low	High	
Notification management	Reactive	Scheduled	Reactive	Proactive	
Monitoring tool use	Rare	Rare	Rare	Common	
Work environment	Mixed/public	Office/home desk	Open-plan/hybrid	Dedicated home	
n	**52**	**61**	**47**	**40**	**200**

- **Passive Consumer**: High screen time, dominated by passive activities such as social media and streaming, with reactive notification behavior.
- **Task-Focused Operator**: Moderate screen time with emphasis on productive work and structured notification handling.
- **Context-Switching Multitasker**: Highest screen time with frequent switching between tasks and high notification reactivity.
- **Self-Regulated Strategist**: Lower screen time with proactive control over digital engagement and strong self-regulation.

4.2 Outcome Differences

Significant differences were observed across clusters in both productivity and attention span. The Self-Regulated Strategist demonstrated the highest productivity and longest attention span, while the Multitasker exhibited the lowest performance.

4.3 Correlation Analysis



The correlation heatmap illustrates relationships among key variables. Screen time showed a moderate negative correlation with attention (r ≈ -0.42), while attention exhibited a strong positive correlation with productivity (r ≈ +0.58). The direct relationship between screen time and productivity was weak.

4.4 Cluster-Based Analysis

Cluster-wise analysis indicates that productivity varies significantly across behavioral profiles. The Strategist and Task-Focused clusters outperform others, reinforcing the importance of structured digital usage.

5. Discussion

5.1 Key Findings

The study reveals several important insights. First, screen time alone is not a reliable predictor of productivity. Instead, behavioral patterns and self-regulation play a more critical role. Second, multitasking significantly reduces attention span, leading to lower productivity. Third, passive consumption and reactive notification behavior contribute to similar negative outcomes, despite differences in usage patterns.

5.2 Mechanisms of Digital Behavior

The findings suggest three underlying mechanisms: cognitive load management, attentional control, and behavioral intentionality. Users who minimize task switching and actively manage their digital environment achieve better outcomes.

5.3 Practical Implications

The results have important implications for digital wellbeing interventions. Rather than applying uniform screen time limits, interventions should be tailored to behavioral profiles. For example, multitaskers may benefit from notification control strategies, while passive users may require activity restructuring.

6. Conclusion

This study demonstrates that digital behavior is multidimensional and cannot be adequately explained by screen time alone. By identifying four distinct digital personality types, the research highlights the importance of behavioral patterns in determining productivity outcomes. The findings support a shift toward personalized, behavior-based approaches in digital wellbeing research and practice. Future studies should incorporate longitudinal designs and objective behavioral measures to further validate the proposed framework.

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Sri Chandrasekarendra Saraswati Vidyapuram, Sector V, Nerul, Navi Mumbai – 400706